Uniform Mortgage Regulation and Distortion in Capital Allocation

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Abstract

The U.S. economy is largely influenced by local features, but some federal policies are spatially uniform across regions. I study the unintended consequences of the uniformity of the national conforming loan limit (CLL) before 2008 on local jumbo mortgage lending. When the national CLL increased, the jumbo share of residential mortgages in low-income counties was significantly reduced relative to high-income counties. I find that banks responded to the national shock by significantly raising jumbo approval rates in low-income counties, consistent with the competition mechanism in which lenders expand jumbo credit to defend market share. The economic magnitude is significant: a county with a $10,000 lower median income is associated with, on average, a 6 percentage-point (or 11.77%) higher jumbo approval rate. The results are not driven by lender-specific changes, borrower quality changes, home price anticipation, or the demand channel. I find that banks in low-income counties lower jumbo mortgage rates and later suffer from worse mortgage performance. Furthermore, smaller and less informed banks expand jumbo credit more aggressively, and riskier borrowers receive more credit. Overall, my results highlight the negative consequences of the uniformity of federal policy in mortgage markets by showing how it can lead to distorted bank lending and reduce the efficiency of capital allocation across regions.

Keywords: Uniform federal policy, Policy implication, Conforming loan limit, Jumbo mortgage, Regional variation, Bank lending

JEL Classifications: G21, R21, R31

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1 Introduction

The U.S. economy is strongly influenced by local features. However, federal policy is often nationally uniform and does not reflect differences in regional economic conditions across the country.[1] Economic theory provides the insight of such uniform pricing: consumers in areas with low costs can subsidize consumers in high-cost areas. However, is the uniform feature of such policies optimal? Does it lead to distorted agency incentives and inefficient capital allocation? In this paper, I analyze the unintended consequences of the nationally uniform conforming loan limit— the maximum dollar amount of a home loan that government-sponsored enterprises (GSE) can guarantee—in the context of U.S. residential mortgage markets, through which most households' borrowing occurs. I specifically examine how bank lending can be distorted by such uniformity across regions, which leads to inefficient credit allocation.

One way the national housing finance system explicitly affects local residential mortgage borrower access to credit is through GSEs, such as the Federal National Mortgage Association ("Fannie Mae") and the Federal Home Loan Mortgage Corporation ("Freddie Mac"). They purchase mortgages directly from the loan originators, and either hold them in their portfolio or issue mortgage-backed securities (MBS) to investors, which constitutes their dominant role in fostering the development of the secondary market. Fannie Mae and Freddie Mac are restricted by law to purchasing single-family mortgages with origination balances below a specific amount, known as the "conforming loan limit" (CLL) that is set annually by The Office of Federal Housing Enterprise Oversight (OFHEO). A mortgage of a size above the CLL (i.e., a *jumbo* mortgage) cannot be purchased by GSEs and thus has lower liquidity and a higher yield. Jumbo mortgages are attractive to banks, in part because of jumbo loans' higher rates, and in part because of wealthy borrowers' extraordinary credit quality and their potential to establish deeper business relationship with banks. Prior to 2008, the CLL was increased annually and was uniform across all regions throughout the U.S., except for Alaska, Hawaii,

[1] For example, the U.S. Postal Service delivers all first-class mails to any customer at a fixed price, independent of location.

Virgin Islands, and Guam.[2] When CLL increases, the share of jumbo loans declines since some old jumbo mortgages become conforming loans under a higher CLL. However, the reduction of jumbo share is different across regions, due to regional heterogeneity of economic development and housing market structures. To interpret, the jumbo share may not be significantly reduced in high-income counties with a sufficiently large number of expensive homes, but it can be dramatically reduced in low-income counties. This regional variation in jumbo share reduction stems entirely from the nationwide uniformity of the CLL that is largely indenpendent of local lending environment and economic forces.[3] I exploit this regional variation in local jumbo markets to examine the direct effects of such spatially uniform pricing of conforming mortgage on bank lending and credit supply distortion across local jumbo markets.

I begin by examining the aggregate credit supply at the county level after the CLL increased at the beginning of 2006. As the jumbo share shrinks after the CLL increases, this effect is especially large in low-income areas where there are fewer expensive houses. Specifically, I focus on jumbo market segment in each county and compute the approval rates considering all banks and credit unions that receive jumbo loan application in that county.[4] I find that, following the increase in CLL, banks expand their jumbo credit supply in low-income counties by approving significantly more jumbo mortgage applications than those in high-income areas. To quantify the economic magnitude of regional variation in raised jumbo approval rates, a county with a $10,000 lower median income is associated with, on average, a 6 percentage-point (or 11.77%) higher jumbo approval rate. A back-of-the-envelope exercise implies a $12.6 billion *additional* jumbo mortgage credit supplied to lower-than-average-income counties during the 2006-2007 period.

[2]Limits for Alaska, Hawaii, Virgin Islands and Guam are 50% higher. Virgin Islands was designated a high cost area in 1992 and Guam in 2001.

[3]Each year the conforming loan limits are based on the national median home prices from October to October reported by the Federal Housing Administration (FHFA), which takes account for all home prices across 3,142 counties in the U.S. Thus, the contribution of single county home prices to the national CLL change can be largely ignored, and the change in nationwide CLL is highly independent to county local economic forces.

[4]Specifically, in forming the sample of jumbo mortgage lenders I include banks regulated by the Federal Reserve, the Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC), thrift institutions, and credit unions.

As a higher CLL makes jumbo mortgages scarce assets and naturally leads to more intense credit market competition, I next examine whether interbank competition acts as a determinant of credit supply increase. Theory provides controversial interpretations. Banks in a concentrated market could encourage more entry in an effort to internalize the benefits of assisting the borrowers (Mayer (1988); Petersen and Rajan (1995)); alternatively, banks with market power may favor established borrowers over new ones, and thus lenders may have less incentive to finance newcomers in a less competitive credit market (Spagnolo (2003); Cestone and White (2003)). My empirical results, in the context of jumbo market, show that the effects of reduced jumbo share on bank lending are particularly acute for counties where the credit market is competitive. This finding is consistent with the view that banks compete for a smaller pool of jumbo borrowers by extending credit supply, and thus create adverse selection problems for their competitors (Dell'Ariccia (2001); Agarwal and Hauswald (2010)).

Next, by utilizing rate spread data from the Home Mortgage Disclosure Act (HMDA) dataset, I show that banks lower the interest rates of jumbo mortgages especially in areas where the credit market competition is more intense. Moreover, a larger increase in jumbo approval rate is associated with relatively poorer loan performance. This association is economically and statistically more significant for banks that have higher exposure to jumbo loan lending. These results further lend support to the competition channel through which banks expand jumbo credit and lower loan price to defend market share.

I also take a number of steps to rule out alternative explanations of the main finding. First, I rule out the possibility that bank-specific changes can drive my results by conducting a within-bank test. Using bank-county-year level data, I add bank-year fixed effects to account for all cross-lender variations that change over time, which eliminates the time-varying bank-specific changes that can explain our results. Intuitively, this test examines whether the same bank lending to the same county behaves differently before and after the new CLL was introduced. Second, I examine whether the change in loan quality can explain the raised jumbo approval rates in low-income areas. In particular, I use two approaches: (i) Estimate the baseline regression using a subsample of borrowers with similar credit quality before and after the CLL increase, and (ii) use a difference-in-difference framework in combination with the propensity score matching methodology over the period of 2007-2008. More details will be discussed in Section 4.3.2. Overall, my results remain robust after controlling for loan quality change. Third, I rule out the possibility that the increased approval rates are driven by higher securitization rates through adding a control variable that captures the county-level securitization intensity. Fourth, I verify that neither house price expectation nor demand channel can explain my findings. Fifth, I estimate a placebo regression one year after the CLL increase and find no statistically significant effect of jumbo share reduction on bank lending. Finally, I conduct a battery of robustness checks and verify that these results are robust to a variety of estimation techniques and variable definitions.

Furthermore, I investigate the substantial heterogeneity of lenders and borrowers across differential characteristics that may be hidden under the documented significant increase of jumbo loan approval rates in low-income counties. In particular, I find that smaller and less informed lenders expand jumbo credit more aggressively by raising approval rates, and the magnitude of this effect increases with the degree of local credit market competition. These results suggest that banks acquire private information through lending in jumbo market so that they can soften price competition through creating adverse selection problems for their competitors (Hauswald and Marquez (2006)). Small banks that are less geographically diversified and less informed banks that have information disadvantage have especially strong desire to defend market shares for fear of being left out by their competitors. Exploiting variations in borrower characteristics, I demonstrate that borrowers receive more credit if they have (i) a higher loan-to-income ratio, i.e., lower credit quality, or (ii) refinancing mortgage applications rather than home-purchasing loans.

This paper contributes to a number of existing literatures. First, it adds value to the stream of literature that studies the effects of uniform federal policies. For example, Hurst, Keys, Seru, and Vavra (2016) examine the impacts of the uniformity of GSE mortgage rates on wealth transfer through regional redistribution and highlight a direct mechanism by which credit market can serve to insure regional shocks. Kulkarni (2016) shows that the regional uniformity of GSE mortgage rates lead to credit rationing. In particular, the lack of regional variation in mortgage rates leads to the credit rationing of marginal borrowers in regions with borrower-friendly laws. My paper complements these findings by highlighting a direct channel through which uniform pricing regime in mortgage market can distort bank lending and lead to inefficient credit allocation across regions.

This paper also enriches the literature on the connection between credit market competition and the strategic use of private information (Dell'Ariccia (2001); Hauswald and Marquez (2006); Agarwal and Hauswald (2010)), entrepreneurship and the formation of new incorporations (Black and Strahan (2002)), credit standards (Ruckes (2004)), the market structure of nonfinancial sectors (Cetorelli and Strahan (2006)), small-firm borrowing costs (Rice and Strahan (2010)), and the supply of complex mortgages (Di Maggio, Kermani, and Korgaonkar (2016)). These papers show convincingly that credit supply shock and credit market competition among banks influence their lending strategies and loan terms. Different from the existing literature, my study investigates how lenders redistribute credit across regions due to a shock triggered by the spatial uniformity of federal policy.

Finally, this paper adds to the emerging literature on understanding the causes and effects of the credit expansion in mortgage markets. Related literature has focused on supply growth in mortgage credit (e.g., Mian and Sufi (2009), Mian and Sufi (2011); Favara and Imbs (2015); Di Maggio and Kermani (2015)) and on mortgage credit demand (Adelino, Schoar, and Severino 2014, 2015, 2016). Different from these studies, this paper contributes to the literature by highlighting a competition channel which can also drive the recent mortgage credit expansion in jumbo market segment. Furthermore, my results establish the heterogeneity in lenders' responses and suggest that banks with liquidity and information disadvantages tend to lend more aggressively and compete with their rivals to defend market shares.

This paper is organized as follows. Section 2 discusses institutional setting. Section 3 describes data and sample. Section 4 presents the main results and the economic mechanism and rules out alternative explanations. Section 5 provides evidence of heterogeneity of lenders and borrowers. Section 6 concludes.

2 Institutional Background and Identification Strategy

2.1 Jumbo mortgage market segment

Jumbo loans are especially attractive to lenders for several major reasons. First, the jumbo/nonjumbo spread, which has varied between 15 and 25 basis points over the past two decades, leads to an enhancement of lender's income.[5] Due to the role of the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac), securitization of residential mortgages has grown rapidly since the early 1980s (Frame and White (2005)). Since the legislative goal of these two government sponsored entities (GSEs) is to promote access to mortgage credit for low- and moderate-income households, they operate under a special charter limiting the size of mortgages that they may purchase or securitize. Any mortgages above this size limit are called jumbo loans and cannot be purchased by the GSEs. As noted in Loutskina and Strahan (2009), some of the increase in yields for jumbos reflects differentials in liquidity since GSEs enhance liquidity for nonjumbo loans but not jumbos.

Second, the extraordinary credit quality of wealthy borrowers makes jumbo mortgage lending continue to be a bright spot for lenders. In contrast to nonjumbo loans, lenders keep jumbos on their balance sheets, in part because of their lower liquidity and in part because they see jumbo mortgages as a safe investment to hold, versus selling them as mortgage-backed securities.

Third, anecdotal evidence suggests that lenders are driven by the incentive of building

[5]For jumbo/nonjumbo spread, see for example Ambrose, LaCour-Little, and Sanders (2004), Loutskina and Strahan (2009), and Adelino, Schoar, and Severino (2014).

long-term connection with jumbo borrowers. Lenders can benefit from this deeper relationship with affluent consumers in various ways, and most of the time they can expand businesses other than mortgage originations. For example, lenders are willing to target jumbo borrowers and sell them other financial products and services, in an effort to expand businesses in the local market.

2.2 Identification strategy

This paper examines the effect of uniform jumbo mortgage limit on bank lending by employing the nationwide change of conforming loan limits (CLLs). As previously discussed, GSEs may only purchase mortgages below the conforming loan size limit.[6] The loan size limit increases every year by the percentage change of the national average of single-family housing prices, based on a survey of major lenders by the Federal Housing Finance Board. Prior to 2008, the size limit was uniform across all counties throughout the U.S., except for high-cost areas including Alaska, Hawaii, Virgin Islands and Guam, where the limit is 50% higher. For example, the CLL for single-family homes experienced a 16% increase, the most significant increase in history, from $359,650 in 2005 to $417,000 in 2006, and this limit is constant throughout the U.S. Because the loan limit changes only as a function of national average home price, local housing market conditions have little contribution to the change.

While counties are different in economic development and housing market structure, the nationwide uniform CLL serves as an instrument for regional variations in local jumbo mortgage shares. Some recent studies, for example, Adelino, Schoar, and Severino (2014) and An and Yao (2016) utilize the CLL as an exogenous instrument for credit access and investigate its impact on home prices and economic outcomes. Different from these studies, I focus instead on the jumbo mortgage segment and investigate credit redistribution across regions.

[6] The GSE guidelines that identify a mortgage loan that conforms to GSEs include not only loan size, but also borrower's loan-to-value ratio, debt-to-income ratio, credit score and history, documentation requirements, etc. Although GSEs may only purchase some of the mortgages below the conforming size limit, none of the jumbo loans can be sold to GSEs. As a result, in this paper the analysis focusing on jumbo market segment is not affected by the conforming loan criteria despite of the size limit.

[Figure 1 inserted here]

Figure 1 illustrates the effects of CLL change as the identification strategy. High-income areas have relatively more expensive houses and more mortgages qualified as jumbos, but low-income areas have much fewer jumbo loans. When the CLL increased from $359,650 to $417,000 in 2006, a proportion of loans that were jumbo loans above the old 2005 CLL became conforming loans in 2006 (the blue parts), and the new jumbo loan shares in the low- and high-income areas are affected differently: in low-income areas with fewer expensive homes, as the red parts show, the new jumbo share is exogenously reduced to a significantly lower level under the new CLL, while the jumbo share in high-income areas is not heavily reduced (in a relative sense) because there are more expensive homes in these areas. However, the number of lenders almost remain at a constant level right after the CLL change. This regional variation is exploited as the identification strategy to examine the effect of jumbo share reduction on bank lending strategy and credit supply, i.e., how lenders in low- and high-income areas respond differently to the increase in the uniform CLL.

3 Data and Sample Selection

The data of mortgage applications and originations are obtained from the Home Mortgage Disclosure Act (HMDA) dataset. The main sample covers loan applications from 2005 to 2007. All regulated financial institutions with more than $30 million in assets, such as commercial banks, credit unions, and mortgage companies, must report required data. The HMDA data include loan applications' information on the lender's identity, the location of the property, the dollar amount of the loan, application year, and whether or not the loan was accepted or sold to a third party. Borrower information is also provided, such as borrower's reported income, race, and gender.

Using HMDA data I compute the county-level and the bank-county-level approval rates (ARs) of jumbo loan applications, as a measure of credit supply to jumbo segment. The county-level AR equals the ratio of all accepted jumbo loans over all jumbo loan applications across all banks in the county, where the ratio is based on either the number or the volume of jumbo loans. The bank-county-level AR equals the ratio of jumbo loans accepted by a bank in a county over all jumbo loan applications to the bank in the county, based on either the number or the volume of jumbo loans.

To control for borrowers' credit risk in a geographical area, I include the average number of the log of the applicant's income in the county, the average loan-to-income ratio, the share of the population that is minority, and the share of female applicants in the property's county. I also include the county-level income growth rate to absorb variation in economic development and mortgage demand. The county-level income per capita and income growth rate are obtained from the Bureau of Economic Analysis. To control for the trend of the house price growth, I obtain the MSA- and state-level housing price index (HPI) from the Federal Housing Finance Agency (FHFA), then classify the counties overlapping with the MSAs and match corresponding HPI with counties. Unmatched counties are matched with the state-level HPI.

Using lender identity, I then merge HMDA data with the bank-level data from the Reports of Condition and Income for commercial banks ("Call Reports"). I follow Loutskina and Strahan (2009) and merge each application with the Call Report from the fourth quarter of the year prior to the mortgage application.[7] All unmatched institutions from the HMDA dataset are then matched manually using the bank's name and county name. The bank control variables include size (log of assets), leverage (the capital-asset ratio), accounting profits (net income to assets), balance-sheet liquidity (investment and traded securities to assets), share of deposit finance (ratio of deposits to total assets), deposit costs (interest expenses on deposits to total deposits), letters of credit in total assets, unused loan commitments in total assets,

[7] To merge with the HMDA bank identification number, I use the Call Report identification number (RSSD ID) for banks regulated by the Federal Reserve (FR), the Federal Deposit Insurance Corporation (FDIC) certificate ID (item RSSD9050 in the Call Report) for banks regulated by the FDIC, with the Office of the Comptroller of the Currency (OCC) ID (item RSSD9055 in the Call Report) for banks regulated by the OCC, with the Office of Thrift Supervision (OTS) ID (item RSSD9037 in the Call Report) for thrift institutions regulated by the OTS, and with the National Credit Union Administration (NCUA) Charter ID (item RSSD9039 in the Call Report) for credit unions regulated by the NCUA.

real estate loans in total assets, and commercial and industrial loans in total assets.

[Table 1 inserted here]

Table 1 presents the summary statistics of the merged datasets in the pre- and post-2006 periods, and for high- and low-income counties separately. I report the means and standard deviations of variable distributions at the county-year level. High- and low-income counties are divided by the median value of county income per capita in pre- and post-2006 periods separately. For high-income counties, the change in approval rates between pre- and post-2006 periods is very marginal, while the change of low-income counties is much larger. The count-(volume-) based approval rate increases from 45.6% (46.6%) in the pre-2006 period to 51.9% (53.5%) in the post-2006 period.

4 Lender Response to Reduced Share of Jumbo Markets

4.1 Econometric model and main results

This section provides main results of how lenders respond to reduced jumbo shares across regions. County median home price measures the overall house price level in a county and thus can be a proxy for the extent to which the county is affected by the CLL limit change. However, if median house price is used as an explanatory variable to explain credit supply, it causes a reverse causality problem and an omitted variable problem. For example, high credit supply to local borrowers can further increase the local home prices. It is also possible that the lender and borrower's anticipation of future home prices can strengthen the association between credit supply and home price. Instead, county median income serves as a better explanatory variable in the specification. There are several reasons for the use of median income: First, as Figure 2 illustrates, county-level median income and median house price are positively correlated; second, the estimation does not suffer a reverse causality problem because credit supply in a county does not affect the contemporaneous county median income; third, other county-specific factors that affect both income and credit supply can be captured by county fixed effects.

[Figure 2 inserted here]

Specifically, I use aggregate county-level data and estimate

$$\begin{aligned} AR_{it} =& a + b_1 CountyIncome_{it} \times Post_t + b_2 CountyIncome_{it} + b_3 Post_t \\ & + Loan\ Controls_{it} + Bank\ Controls_{it} + County\ Controls_{it} + c_i + \theta_t + \epsilon_{it}, \end{aligned} \tag{1}$$

where AR_{it} is the jumbo mortgage approval rate in county i in year t. Importantly, I compute AR by focusing on jumbo applications with the loan amount above $417,000 for all sample years instead of post-2006 period only. This attempt helps alleviate the concern that the pools of jumbo borrowers before and after 2006 are different.[8] Two measures of approval rates are constructed: the first one equals the fraction of approved jumbo loan applications to total jumbo loan applications made by all lenders in county i in year t, where the fraction is based on the number of jumbo loans; the second measure is similar, but the fraction is based on the volume of jumbo loans. $CountyIncome_{it}$ is the median income in county i in year t. $Post_t$ is a dummy variable equal to one for all years in or after 2006, and zero prior to that. The coefficient of interest is b_1, which measures the change in the approval rates between high-income counties and low-income counties before and after the CLL change in 2006.

In the estimation specification, I include three sets of control variables. The first set includes the following average county-level characteristics of the loan applicant pool obtained from HMDA data: the log of applicant income, the ratio of the loan size to applicant income (loan-to-income ratio), and the shares of female and minority loan applicants in the county.[9]

[8] I also estimate specifications using the strict cutoff of CLL in 2005 to define jumbo loan borrowers, i.e., loans above $359,650 are defined as jumbo loans in 2005, and find similar results.

[9] I construct county-level income and loan-to-income ratio by averaging across all of the mortgages in a county in a given year.

The second set includes average bank characteristics from the Call Report: the log of bank total assets, leverage (the capital-asset ratio), accounting profits (net income to total assets), balance-sheet liquidity (investment and traded securities to total assets), share of deposit (ratio of deposits to total assets), deposit costs (interest expenses on deposits to total deposits), letters of credit in total assets, unused loan commitments in total assets, share of real estate loans to total assets, and share of commercial and industrial loans to total assets. Third, I also control for the county-level income growth rate and the housing price index (HPI) growth rate and its lagged value. Importantly, Equation (1) includes county fixed effects (c_i) to control for any county-specific credit demand shocks and year fixed effects (θ_t) to control for time-varying factors that are constant across counties. As there may be additional autocorrelation in the residual, I cluster the standard errors by county.

[Table 2 inserted here]

Table 2 presents the results. The variable of interest is the interaction of $CountyIncome$ and $Post$ dummy. Column 1 shows that count-based approval rates significantly increase more in low-income counties after the CLL change at the beginning of 2006. The inclusion of county fixed effects demeans $CountyIncome$ variable. The result implies that a standard deviation decrease in county median income (7.972×$'000) increases the jumbo approval rate, on average, by 4.78 percentage points. This effect is not trivial compared to the unconditional mean approval rate of 50.96%. Column 2 adds borrower, lender and county controls and shows that the coefficient of interest remains economically and statistically significant. Columns 3 and 4 replace county median income with its logarithm value in the estimation regressions and show that the coefficient of interest remains negative and statistically significant with a much larger magnitude. Columns 5 through 8 estimate the same baseline regression using the volume-based approval rate as the dependent variable. The coefficient of interest remains statistically significant and become slightly larger in magnitude relative to the results in columns 1 through 4. These results indicate that, after the CLL increases, jumbo loan approval rates in low-income counties are significantly larger than those in high-income counties. This finding suggests that in low-income areas where the reduction of jumbo loan share is larger, lenders tend to expand credit supply through increasing the approval rate. Panel A of Figure 3 illustrates the empirical finding in Table 2. After the increase of CLL in 2006, the average county-level jumbo approval rate in low-income counties raised by about 6.3%, from 45.6% to 51.9% which exceeds the average approval rate in high-income counties (50.8%) in post-2006 period.

[Figure 3 inserted here]

Another possible explanation for the increase in 2006 jumbo approval rate could be due to the systematic mortgage credit expansion to low-income counties. Panel B of Figure 3 illustrates the average county-level approval rates for mortgages that are smaller than the CLL. As a sharp comparison with Panel A of Figure 3, the average county-level non-jumbo approval rate in low-income counties did not raise significantly, which can help mitigate the concern of the systematic mortgage credit expansion to low-income counties in 2006.

4.2 Economic mechanism

4.2.1 Determinants of lender responses: competition channel

Having documented the increase in jumbo approval rate after jumbo shares decline, this subsection examines in detail the underlying economic mechanism. As the CLL change triggers a jumbo market share reduction that is exogenous to local economic conditions, the credit market for jumbo mortgages becomes more competitive since lenders face a smaller pool of potential jumbo borrowers. This effect is especially stronger in low-income counties.

In the context of bank-firm relationship, theory offers competing hypotheses about how interbank competition ought to influence access to bank credit. For example, as Mayer (1988) and Petersen and Rajan (1995) suggest, banks with market power should guarantee more entry so that they can internalize the benefits of assisting the firms at later stage if such entrants turn out to be successful. In addition to this channel, Spagnolo (2003) and Cestone and White (2003) show that the less competitive the conditions in the credit market, the lower the incentive for lenders to finance newcomers, because banks with market power may favor their established borrowers over new ones. In this paper, I focus on the jumbo loan market in which the lending mechanism may differ from the relationship lending to the firm. It is not certain whether jumbo mortgages work as "transaction loans" (i.e., loans that involve "arm's length" transactions), or "relationship loans". Thus, it remains as an important empirical question to examine how the competitiveness of the jumbo loan credit market affects the behavior of lenders.

This subsection empirically tests the competition channel through which the approval rate increase can be explained. I first conduct a test to examine the impact of lender competition in jumbo market by constructing a county-level local competition measure, jumbo Herfindahl-Hirschman Index (Jumbo HHI) that is defined as the sum of squared banks' market shares of jumbo loans in a given county, where the shares are based on the number of accepted jumbo loan applications.[10] One can be concerned that counties where credit markets are more competitive tend to be the ones with higher income, so the heterogeneity in the effect of reduced jumbo share captures the effect of income variation and not difference of competition. To mitigate this concern, I then conduct a test based on a subsample that includes only high-income counties. This test more directly explores the variation of competition across counties within a high-income subsample, and provides robustness of the effect of competition on credit supply increase.

[Table 3 inserted here]

Table 3 presents the results. Panel A reruns the baseline regression of Equation (1) by controling for the county-level jumbo competition measure HHI in the estimation model. The coefficient on the competition measure in column 1, -0.173, suggests that moving from fully competitive (i.e., HHI $= 0$) to fully concentrated (i.e., HHI $= 1$) would cut jumbo approval rate

[10] I also construct a similar HHI measure, where the shares are based on the volume of accepted jumbo loan applications, and obtain similar results.

by 17.3 percentage points. This magnitude is substantial relative to the unconditional mean of jumbo approval rate, 50.96%. Columns 3 and 4 confirm the robustness of the coefficient on the interaction term to the use of volume-based competition measure.

Panel B of Table 3 presents the results based on the subsample of high-income counties. I find that, for low-competition counties in this subsample, the coefficient of the interaction term is statistically insignificant (column 1), but it turns statistically significant at the 1% level for the group of high-competition counties (column 2). The results are robust to the use of volume-based approval rate as the dependent variable (columns 3 and 4).

Overall, Table 3 provides confirmative evidence that the jumbo share effect is particularly acute for counties where the jumbo loan market is competitive. Given a same reduction of jumbo market share, lenders operating in highly competitive markets tend to raise approval rates more than lenders operating in less competitive markets. This finding is consistent with the spirit of empirical evidence in the context of bank-firm relationship, which documents that new borrowers face greater difficulty gaining access to credit in markets with concentrated lenders than in more competitive markets (Cestone and White (2004); Cetorelli and Strahan (2006)).

4.2.2 Loan pricing

If the increase in jumbo approval rate is caused by lender competition, it can be reflected in the loan pricing. Specifically, if the reduction of jumbo loan borrowers is larger in low-income areas while the number of lenders remains relatively stable, intense competition between lenders may push down the jumbo mortgage rate to defend jumbo loan market share. HMDA data provides a certain extent of mortgage-level price information that takes the form of a "rate spread". Lenders must report the spread (difference) between the annual percentage rate (APR) on a loan and the rate on Treasury securities of comparable maturity–but only for loans with spreads above designated thresholds.[11] So rate spreads are reported for some,

[11] The thresholds vary across borrower and mortgage characteristics. See, for example, https://www.ffiec.gov/ratespread/newcalc.aspx for more information.

and not all, home loans that have high rates.

Exploiting the rate spread data, I test the above hypothesis by estimating

$$\begin{aligned} RS_{it} =& a + b_1 CountyIncome_{it} \times Post_t + b_2 CountyIncome_{it} \\ &+ Loan\ Controls_{it} + Bank\ Controls_{it} + County\ Controls_{it} + c_i + \theta_t + \epsilon_{it}, \end{aligned} \tag{2}$$

where RS_{it} is the mean or median value of jumbo mortgage rate spreads in county i in year t. $CountyIncome_{it}$ and $Post_t$ are defined as in Equation (1). c_i, θ_t are county-specific fixed effects and year fixed effects, respectively. Standard errors are clustered at the county level. If large reduction of jumbo loan borrowers in low-income areas induced high competition between lenders, one can expect to see a positive b_1, i.e., a lower mean or median value of rate spread for jumbo loans in low-income areas in the *Post* period.

[Table 4 inserted here]

Table 4 reports the results. The dependent variable in columns 1-4 (5-8) is the median (mean) value of jumbo loan rate spread in a given county in a year. Column 1 shows that the coefficient of the interaction term, 0.005, is statistically significant at the 5% level. It suggests that after the new CLL in 2006 became effective, a decrease of \$10,000 median county income value is, on average, associated with a 5 basis points drop in the rate spread for jumbo mortgages. Column 2 confirms this finding by including a full set of borrower, county, and bank controls. Columns 3 and 4 test its robustness using the log value of county income and find similar results. Columns 5-8 use the mean value of jumbo loan rate spread as the dependent variable and further confirm this finding. Overall, results of Table 4 lends support to the competition channel that lenders compete for a smaller market share and lower the jumbo mortgage price for borrowers.

4.2.3 Proxy for loan performance

Do lenders compete more aggressively as a response to reduced jumbo loan borrowers because they simply act to defend market share or because they have better information about borrowers? The competition channel indicates that banks can simply expand their jumbo credit without carefully screening borrowers, which can result in relatively poor performance of jumbo loans. In contrast, fewer mortgages are qualified as jumbo loans after the new CLL, and thus bank's capacity constraint can be less binding and they can obtain better information about borrowers. If this is the case, banks are able to screen borrowers more carefully and price the loans more precisely. To investigate this alternative "capacity constraint" hypothesis, I test how the increase of approval rate affects mortgage performance.

I again estimate panel regressions, although I measure the data by bank-year rather than county-year. Regarding residential mortgage performance, the Call Report provides data on non-performing 1-4 family loans (NPL=1-4 family loans 90 or more days past due plus loans no longer accruing interest) and 1-4 family loans charge-offs. Specifically, I construct four measures of mortgage performance: NPL/total 1-4 family loans, NPL/total 1-4 family loans (constructed using only first liens), family loans charge-offs/total family loans, and family loans charge-offs/total loan charge-offs. In particular, the last variable captures both family loans performance and key aspects of overall lending environment. For example, when the economy is bad, family loans perform relatively poorly because bad economy pushes down bank loans in general, not because banks give out bad family loans. Thus, the last variable addresses this concern by teasing out the relative performance of family loans to overall bank loans.

Specifically, I estimate the following regression specification

$$Performance_{jt} = a + b_1 Jumbo\ AR\ Increase_{jt} + Bank\ Controls_{jt} + \zeta_j + \theta_t + \epsilon_{jt}, \qquad (3)$$

where $Performance_{jt}$ is one of the four performance measures defined above for bank j at the end of year t. $JumboARIncrease_{jt}$ is the percentage change in jumbo loan approval rate for bank j from year $t-1$ to year t. b_j, θ_t are bank-specific fixed effect and year fixed effect, respectively. I cluster at the bank level for standard errors and I estimate the models over the period 2005-2008. In addition, I construct a subsample of "intensive" jumbo loan lenders, which defines "intensive" by using the fraction of a bank's issued jumbo loans over total issued family loans. In this subsample, we include only the bank-years in which the jumbo fraction is above its median value.

[Table 5 inserted here]

Table 5 reports the results. To streamline the table, I report only the coefficients on the increase of jumbo approval rates ($JumboARIncrease$). Panel A of Table 5 reports the results of the full sample. The coefficient on $JumboARIncrease$ suggests that an increase of jumbo approval rate is associated with a higher level non-performing family loans. However, the coefficients for the family loans charge-offs are not economically or statistically significant. More importantly, Panel B of Table 5 focuses on the intensive jumbo mortgages lenders and shows that the positive relation between the increase of jumbo loan approval rates and bad loan performance is stronger, both economically and statistically. For example, the coefficient in column 1 increases from 0.0004 (Panel A) to 0.0013 (Panel B). The coefficient on $JumboARIncrease$ in column 4 of Panel B increases to 0.0081 and becomes statistically significant at the 1% level. The economic magnitude is large: a 10% increase in jumbo approval rate is associated with an 8.1 basis point increase in the ratio of family loans charge-offs relative to total loan charge-offs. These results indicate that banks with larger exposure to jumbo loan lending exert stronger effect of raised jumbo approval rates on bad loans, which is consistent with the competition channel that banks compete more aggressively for market share without carefully screening borrowers.

4.3 Alternative explanations and robustness checks

Although the identification strategy and county fixed effects resolve several empirical concerns by exploiting the exogenous reduction of jumbo market shares, I address some remaining concerns in this section.

4.3.1 Lender characteristics change

The findings of increase in jumbo mortgage originations in low-income counties is consistent with the view that lenders compete for the scarce asset. However, this finding could be driven by the fact that lenders in low-income counties have different characteristics after the CLL change in 2006, such as better credit availability. To test this notion, I run a specification at the bank-county-year level and add bank-year fixed effects so that I can focus on the same bank lending to the same county before and after the new CLL, and evaluate the difference in lending. This approach also acts as a very strong robustness test for the county-level regression reported earlier because I now focus on a more homogeneous sample of lenders and can also fully account for potentially confounding factors that can impact lending decision, such as credit supply.

When conducting this within-bank test, I evaluate the CLL effect on the same bank lending to the same county. Therefore, this test removes potential biases from unobservable bank characteristics from the credit supply side. Specifically, the regression model is as follows:

$$\begin{aligned} AR_{ijt} =& a + b_1 CountyIncome_{it} \times Post_t + b_2 CountyIncome_{it} + b_3 Post_t \\ &+ Loan\ Controls_{ijt} + County\ Controls_{it} + c_i + \eta_{jt} + \theta_t + \epsilon_{ijt}, \end{aligned} \tag{4}$$

where AR_{ijt} is the jumbo mortgage approval rate by bank j in county i in year t. I compute approval rates based on jumbo loan applications in a range of \$417,000—\$600,000 for both 2005 and 2006-07 periods, so that I can compare similar borrowers in both periods. $CountyIncome_{it}$ and $Post_t$ are defined as in Equation (1). c_i is county-specific fixed effects. Importantly, I include bank-year fixed effects (η_{jt}) to control for any time-varying shocks to a bank, including credit supply change and any other factors that may affect lending decision. Standard errors are double clustered at the county and bank levels.

[Table 6 inserted here]

Table 6 reports the results of the within-bank test. I again find that banks increase jumbo loan originations to low-income counties in the post-2006 period. After controlling for county, year, and bank-year fixed effects, the results imply that a $10,000 decrease in county median income increases the jumbo approval rate, on average, by 100 basis points after the new CLL becomes effective (columns 1 and 5), and the results remain robust after controlling for county-specific and loan characteristics (columns 2 and 6). Even after additionally controlling for house price trend, the coefficients remain statistically significant (columns 4 and 8). These results strongly support the view that lenders lend more aggressively after the jumbo share declines.

4.3.2 Borrower quality change

Although in approval rate calculation I focus on similar groups of jumbo borrowers with the loan amount above $417,000 for both 2005 and 2006-07, there still might be a potential concern of differential borrower quality: If the pool of jumbo borrowers in 2006 was better in quality than those in 2005, the increase of approval rate may not be a result of the reduced jumbo share but rather a reflection of better borrower quality.

I test for such concerns by comparing the approval rates for the post-2006 jumbo loan borrowers and the subset of 2005 jumbo loan borrowers that have similar characteristics with post-2006 borrowers. Specifically, I use the lowest reported applicant income and the highest loan-to-income (LTI) ratio among jumbo loan applications in 2006 as thresholds, and pick 2005 jumbo loan applicants that have higher-than-06-lowest income *AND* lower-than-06-highest LTI ratio (both adjusted for inflation rate) to form the subset of borrowers. Then I re-calculate the county-level approval rate in 2005 based on the subset of borrowers in each county in 2005. If the borrower quality concern is the case, one would expect to see a similar approval rate on the subset of 2005 jumbo loan borrowers who had similar characteristics with 2006 jumbo loan borrowers. However, the results in Table 7 show the opposite. Columns 1-4 show that the impact of reduced jumbo share on bank lending after 2006 remains significant, as the coefficient of the interaction term is statistically significant. The results are similar for the volume-based measures of approval rates (not reported).

[Table 7 inserted here]

One may still worry that the increase in jumbo mortgage origination can be a result of other borrower or lender characteristics or some county-specific factors, in addition to income and LTI ratio. To further mitigate this concern, I then exploit the effect of an event of the county-level conforming loan limit changes at the beginning of 2008. The national conforming loan limit for mortgages that finance single-family one-unit properties remained constantly at $417,000 during 2006-2007, with limits 50 percent higher for four statutorily-designated high cost areas: Alaska, Hawaii, Guam, and the U.S. Virgin Islands. Beginning in 2008, various legislative acts increased the loan limits in certain high-cost counties in the United States to reflect local price differences. More specifically, there are two sets of loan limits: "General" and "High-Cost". The "High-Cost" areas are determined by Fannie Mae's regulator, the Federal Housing Finance Agency (FHFA). The Economic Stimulus Act of 2008 temporarily increased the loan limits in high-cost areas. A total of 293 counties were determined by FHFA as high-cost areas and thus utilized various CLLs higher than $417,000 for mortgages to finance single-family one-unit properties.[12] Other counties that were not determined as high-cost areas are "General" areas. Then, the Housing and Economic Recovery Act (HERA) of 2008 permanently changed Fannie Mae's charter to expand the definition of a "conforming loan" to include "high-cost" areas on loans originated on or after January 1, 2009. As a result, for those counties determined as high-cost areas and thus had raised CLL, the potential pool

[12]The map of the high-cost areas in 2008 is shown in Figure A1.

of jumbo loan borrowers shrunk and the competitiveness increased given a relatively steady number of lenders in the area.

To evaluate the effect of the determination of high-cost areas, I first identify control counties that are highly similar to the high-cost areas but are unaffected by this determination. Specifically, I use comprehensive information on county-level socioeconomic, borrowing, and lending characteristics to find similar control samples before the determination of high-cost areas. Second, to further establish the empirical robustness of this approach, I follow Abadie and Gardeazabal (2003) and construct a synthetic control sample loan by loan, by selecting similar loans that resemble relevant observable loan characteristics. For each of the loan applications submitted in the "treated" counties, i.e., the counties that were determined as the high-cost areas, I identify a loan application most similar to it that was submitted elsewhere in the country over the year. Once a loan application is matched with one in the treated area, I remove it from the potential pool of control loan applications. The full list of variables considered for both county- and loan-level matching is summarized in Panel A of Table 8. The panel shows that for each observable characteristics the samples have very similar properties.

[Table 8 inserted here]

The basic county-level regression specification based on a classic difference-in-difference framework has the following form:

$$\begin{aligned} AR_{it} = & a + b_1 Treated_i \times Post_t + b_2 Treated_i + b_3 Post_t \\ & + Borrower\ Controls_{it} + Bank\ Controls_{it} + County\ Controls_{it} + c_i + \theta_t + \epsilon_{it}, \end{aligned} \tag{5}$$

where AR_{it} is the approval rate in county i in year t. $Treated_i$ is a dummy variable that takes the value of one if county i is determined as a high-cost area and zero otherwise. $Post_t$ is a dummy variable equal to one for all years in or after 2008, and zero prior to that. Borrower and bank control variables listed in Panel A of Table 8 are county-level averages. The coefficient of interest is b_1, which measures the change in the approval rates between treated and control counties before and after the high-cost determination in 2008.

The results are reported in columns 1-6, Panel B of Table 8. Even with a small matched sample comprising 154 county-year observations, the coefficient of the interaction term is still significant at the 5% level, and it is robust to the inclusion of various control variables and county and year fixed effects. This finding shows that after the high-cost area determination, the treated counties that had a reduced pool of jumbo loan borrowers experienced an increased jumbo credit supply.

Then I estimate loan-level regressions on a matched sample of loan applications. Particularly, the specification has the following form:

$$\begin{aligned} Accepted_{ijt} =& a + b_1 Treated_i \times Post_t + b_2 Treated_i + b_3 Post_t \\ & + Borrower\ Controls_{ijt} + Bank\ Controls_{ijt} + County\ Controls_{it} \\ & + c_i + \theta_t + \gamma_{Bank} + \epsilon_{ijt}, \end{aligned} \tag{6}$$

where subscripts i, j, and t denote counties, loan applications, and years, respectively. $Accept_{ijt}$ is a dummy variable that takes the value of one if the application is accepted and zero otherwise. $Treated_i$ is a dummy variable that takes the value of one if the application is submitted in county i that is determined as a high-cost area, and zero otherwise. Borrower- and bank-specific controls are based on each loan application. I also control for county, year, and bank fixed effects.

Columns 7-9, Panel B of Table 8 report the loan-level regression results. The coefficients of the interaction term are positive and highly significant, which implies that the loan application in the treated counties after the determination in 2008 is more likely to be accepted. Overall, the results are consistent with the findings in Table 2, which suggests that our results are not driven by potential changes in loan quality.

4.3.3 Securitization rate

Could the increase in jumbo mortgage approval rate be driven by the enhanced bank liquidity due to high securitization rate? This is possible if the majority of accepted loans below CLL are conforming loans, and banks sell conforming loans due to the secondary market activities of the GSEs which further increases banks' balance sheet liquidity. Even after the within-bank tests and the results with bank-year fixed effects, I still conduct an additional test to address this concern.

I include a county-level aggregate securitization rate as an additional control variable that proxy for the average banks' balance sheet liquidity in each of the counties. Specifically, in each year I calculate the securitization ratio of the number of securitized mortgages over total number of accepted mortgages for each bank, then in each of the counties I calculate the weighted securitization ratio considering all the banks that are operated in the county, where the weight is defined as number of mortgages issued by each bank in a given county over the total issued mortgages in that county.[13] This variable controls for the regional variation in average banks' balance sheet liquidity at the county level.

If the increase of credit supply were driven by the increase of bank liquidity, then county securitization rate as a control variable would absorb much variation in approval rate changes, leaving the variable of interest less significant. However, columns 5 and 6 in Table 7 show that after controlling for county securitization ratio, the coefficient of interaction term remains negative and statistically significant. In addition, the magnitude of the coefficient is even larger than the results in Table 2.

[13] To precisely capture the effect of CLL increase on higher securitization rate of nonjumbo loans, I construct a similar measure of county securitization rate that only involves nonjumbo loans, and use it as an additional control variable in the baseline specification. This variable captures the regional variation in the increased number of securitized nonjumbo loans due to the effect of CLL change. After controlling for this variable, I obtain very similar results as in columns 5, 6 and 11, 12 of Table 8.

4.3.4 House price expectation

Another possible alternate explanation for the increase in jumbo approval rate could be due to an expectation of the increase in future house prices. Higher house price growth expectations lower the estimated loss given default, thereby enabling lenders to increase credit supply and target riskier clients (Mian and Sufi (2009)). If this expectation-based hypothesis were the case, then the finding of credit supply increase would be more prevalent in counties with higher expectation of house prices.

One way to test this hypothesis is to focus on areas where the expectations-based channel is not prevalent. Glaeser, Gyourko, and Saiz (2008) point out that areas with extremely elastic housing supply are unlikely to have large increases in house price growth expectations because any upward pressure on house prices will lead to increased construction and thereby a higher quantity of housing stock. Therefore, in very elastic counties house price growth is bounded by the quick adjustment in housing stock.

I test the expectations-based hypothesis by focusing on counties with high housing supply elasticity. I collect data on housing supply elasticity from Saiz (2010) at the MSA level, and assign the elasticity measure to counties overlapping with the MSAs. This measure of elasticity is based on the percentage of land which cannot be developed for housing, and captures the extent to which the area is land-constrained by its geography. Saiz (2010) computes and ranks the measure of supply elasticities for 95 MSAs. I focus on the counties with high housing supply elasticity measures in the top tercile (where the measure of supply elasticity is greater than 2.21).[14]

[Table 9 inserted here]

Panel A of Table 9 provides results for the high-elasticity subsample after running the baseline regression in Equation (1). The results show no significant change in the coefficient of the interaction term. The coefficient remains statistically and economically significant for

[14] See Saiz (2010) for more details on the measure of housing supply elasticity.

both count-based and volume-based approval rates. This finding indicates that the increased jumbo approval rates in low-income counties after the CLL change are not driven by areas with low housing supply elasticity, thereby suggesting evidence against the increasing house price expectation hypothesis.

4.3.5 Demand channel

One may have a concern that the increase in jumbo loan approval rate can be driven by the income-based demand hypothesis which argues that the growth in individual mortgage size is strongly positively related to the growth in household income (Gerardi, Rosen, and Willen (2010); Adelino, Schoar, and Severino (2016)). If this were the case, then the counties with low household income growth should be less likely to experience a growth in mortgage credit.

To test this hypothesis, I obtain data on county-level per capita income and the growth in per capita income from the Bureau of Economic Analysis over the sample period 2005-2007. Then I focus on the counties with low per capita income (growth), i.e., the counties with per capita income (growth) lower than its median value of the full sample. In particular, the counties with low income growth have average annual nominal growth rate of 1.27%, which suggests a real growth rate of -1.89% (the average inflation rate during this period is 3.16%). Correspondingly, if the increase of credit supply can be explained by the income-based demand hypothesis, then we should not find such jumbo mortgage credit growth in areas with low income growth.

Panels B and C of Table 9 present the results. Panel B (Panel C) rerun the baseline regression in Equation (1) for the counties with low per capita income (growth). In both Panels B and C the coefficients of the interaction term remain negative and statistically significant, which confirms that even in the counties with negative real income growth rate, the increase in jumbo approval rate is still significant. Thus, it cannot be that the results are driven by the income-based demand explanation.

4.3.6 Placebo test

Having put forward the idea that the increase in jumbo approval rate is associated with the reduction in jumbo share caused by the CLL change in 2006, the main results in Table 2 are in line with this view, but it is possible that the significant increase of jumbo loan credit is not specific to this sample period. If the credit supply can be explained by other factors instead of the CLL change, we may expect to find such growth in jumbo mortgage credit during period when there is no CLL change.

To show the uniqueness of the impact of the CLL change on jumbo mortgage credit supply, I perform a placebo test on data over Jan 2006-Dec 2007. This period starts right after the new CLL became effective at the beginning of 2006, and ends before the CLL change in "High-Cost" areas determined by the FHFA beginning in 2008. Therefore, the CLL remained unchanged for all counties during this placebo period. However, I assume that there is a CLL increase at the beginning of 2007 and recalculate the independent variables accordingly. For example, Post indicator during this placebo period is equal to one for 2007, and zero for 2006. Particularly, the placebo regression runs the baseline specification in Equation (1) on the placebo period using redefined independent variables.

[Table 10 inserted here]

Table 10 presents the results. Columns 1 and 2 show the baseline regression and the placebo regression for the count-based approval rate as the dependent variable. Column 3 then presents the result from the one-sided t-test that examines whether the coefficient of the interaction term in the baseline regression (column 1) is significantly larger in magnitude than that in the placebo specification (column 2). When we compare columns 1 and 2, it becomes clear that most of the results are absent in the placebo period. Not only is the statistical significant of the coefficient absent in column 2, but also the magnitude shrinks (-0.005 in column 1 versus -0.001 in column 2). The very low p-value in column 3 formally shows that there is no significant increase of jumbo loan credit in low-incomeareas when the CLL has not changed. Columns 4-6 use the volume-based approval rate as the dependent variable and confirm the robustness of the results.

Overall, Table 10 reflects the uniqueness of the relationship between jumbo approval rate increase in low-income areas and the CLL change. This supports the claim that the impact of reduced jumbo mortgage share on jumbo credit supply either appeared or strengthened, in economic and statistical terms, due to the CLL change.

4.3.7 Other robustness checks

Table 11 presents a battery of robustness tests to check whether or not our main results are sensitive to changes in estimation techniques or variable definitions. First, if credit supply has a trend over our sample years, the regression estimation would not capture the *real* impact of CLL change on credit supply. Columns 1 and 5 show regression results where I include a linear time trend that is identical across all counties. In order for the time trend to be reflected in the regression, I drop year fixed effects. The estimations show that the results still hold. This suggests that the coefficient of the interaction term is not driven by the overall direction the credit supply moves across time.

[Table 11 inserted here]

Next, I verify that my findings are not an artifact of state-specific trends across time. Columns 2 and 6 in Table 11 show the results of regression specifications where I control for state-specific time trends. These results survive after including state-specific time trends that allow each state to have different trends in jumbo loan credit supply that could have coincided with the impact of CLL change on local areas.

In columns 3 and 7 I exclude counties with the lowest (i.e., bottom quartile) median income and rerun the baseline specification. In this way I check whether our results are driven by extremely high approval rates for jumbo loans in very-low-income counties where there are only a few jumbo loan applications. This turns out not to be the case and the results are robust to the exclusion of very-low-income counties.

Furthermore, I exclude all extreme values in the 1_{st} and 99_{th} percentile of the distribution of $ApprovalRate$ for both count- and volume-based measures. The results in columns 4 and 8 show that our findings do not appear to be sensitive to the way I exclude extreme values. The coefficients of interaction terms remain negative and statistically significant.

The dependent variable in columns 1-4 is number-based jumbo loan approval rate. Columns 5-8 use volume-based approval rate as the dependent variable and further confirms its robustness. In addition, I use the logarithm of county income in the regressions and confirm the robustness. The results are reported in Table A2.

5 Heterogeneity in Lenders and Borrowers

The analysis thus far has focused on the average response of lenders to jumbo mortgage share reductions, suggesting that lenders significantly raise jumbo approval rates in counties where the jumbo share reduction is larger. In addition, it is important to understand heterogeneity in lenders' responses to CLL change, and the difference in approval rates for heterogeneous borrowers. For instance, locally concentrated lenders may be especially sensitive to changes in jumbo market shares; less wealthy and liquidity constrained borrowers may obtain more credit when lenders increase jumbo credit supply. In this section, I aim to identify important heterogeneity in lenders' responses to jumbo mortgage share reductions and heterogeneity in borrowers' characteristics.

5.1 Heterogeneous lenders

While the effect of the CLL change differs across regions, lenders in each region may also vary in characteristics such as liquidity and local informativeness and thus can differ in their responses to the policy shock. As noted in Loutskina and Strahan (2011), jumbo loans are (i) less liquid in the capital market than conforming loans, since the latter can be securitized through GSEs and trading of mortgage-backed securities (MBSs) in the secondary market, and are (ii) more private-information-intensive because they are more costly to sell. Therefore, the importance of jumbo market to banks may vary with bank-specific conditions. For example, small banks may differ from large banks in reacting to the CLL change due to differentials in geographic diversification and business bases; banks with differential informativeness of local markets may have different incentives to defend market share.

5.1.1 Lender size: small vs. large banks

I first exploit lender size. To classify banks as small or large, I divide the sample of banks based on total assets in 2005 (the first year in the sample period of my analysis). A bank is classified as *large* if its total assets is above the top one percent cutoff of the assets distribution, and classified as *small* if it is below the top one percent cutoff.

I have several reasons to exploit variation in bank size: (i) Small banks are more likely to rely on the originate-and-hold business model and thus keep jumbo mortgages on their balance sheets, which lowers the liquidity of their portfolio; (ii) as jumbo mortgage rates are higher relative to conforming loans and thus serve as an important source of income for small banks that do not have many other sophisticated means in generating profits; (iii) small banks tend to be more locally concentrated, therefore they have stronger desire to maintain business connection with their local wealthy borrowers since they cannot easily find substitution in other regions.

[Table 12 inserted here]

Panel A of Table 12 tests the hypothesis that the CLL policy shock should affect small banks more than large banks by running the baseline specifications for small banks (columns 1-4) and large banks (columns 5-8) separately. In columns 1-4 (columns 5-8) I only focus on the subsample of jumbo loan applications to small (large) banks and recalculate the approval rate and the corresponding borrower characteristics as control variables. The negative and significant coefficient on the interaction term for all columns 1-4 confirms that the jumbo share reduction leads to a higher approval rate of jumbo loans for small banks, and this result is robust to the inclusion of a large set of control variables. Columns 5-8 show that the top one percent largest lenders do not increase jumbo credit supply significantly in low-income areas after the CLL change. The results in Table 12 suggest that small banks lend more aggressively than large banks when the pool of jumbo loan borrowers shrinks.

5.1.2 Lender informativeness

I next exploit informativeness heterogeneity across bank-county pairs. If banks differ in the extent to which they are informed of local credit markets, they can differ in the strategic use of information to defend market share of jumbo loans.

Theory suggests that the strategic role of acquiring information in jumbo loan segment may interact with the structure of the banking industry. Banks lending in a competitive credit market can differ from those lending in a relatively concentrated market. As jumbo loan market is information-intensive (Loutskina and Strahan (2011)), banks' acquisition of proprietary information serves a dual role. First, by conducting credit assessment, banks can attract customers from their rivals, and thus extending market share. Second, it allows banks to create an adverse selection problem for their competitors, thereby softening price competition (Hauswald and Marquez (2006)).[15] I expect that the severity of this problem increases with the degree of credit market competition.

Using the CLL change as an exogenous event that triggered a sudden reduction in jumbo loan shares, I compare the pre-2006 and post-2006 periods in a first-difference cross-sectional setting. By doing so I can test whether the interaction of banks' informativeness and market competitiveness is associated with the increase in jumbo approval rate. To measure the bank's informativeness of a given county, I follow De Haas and Van Horen (2012) and use the log of the number (or volume) of jumbo loans that a bank provided to a county in 2005 (before

[15] As noted in Dell'Ariccia (2001), for each bank the adverse selection problem stems from its inability to discriminate between new borrowers and borrowers rejected by its competitors.

the CLL change at the beginning of 2006). The log-transformation captures the decreasing marginal impact of number (or volume) of loans on bank's informativeness. To measure competitiveness of the credit market, I compute the Herfindahl-Hirschman index (HHI) in 2005 by summing up the squared banks' market shares in a county, where market share of the bank is defined as the ratio of the number of jumbo loans issued by the bank over the total number of issued jumbo loans by all banks in the county in 2005.[16]

I use fixed effects to address the unobservable heterogeneity concern. In order to precisely control for changes in credit demand at the county level, I first use county fixed effects to focus on differences across banks within counties (see Khwaja and Mian (2008), Schnabl (2012), and De Haas and Van Horen (2012) for a similar application). This is important because the CLL change may impact the jumbo loan credit demand to varying degrees in different counties. Second, since banks are active in multiple countries, I include bank fixed effects to control for bank-specific factors that might affect any changes in lending. The combination of bank and county fixed effects allows me to focus on the informativeness measure that links bank i with county j. Since these fixed effects capture (un)observed characteristics of banks and destination counties, concerns about omitted-variable bias should be quite limited.

In particular, the cross-sectional specification is

$$\begin{aligned} \Delta JumboAR_{ij} = & \beta \cdot Inform_{ij} \cdot HHI_j + \gamma \cdot Inform_{ij} \\ & + \zeta \cdot \Delta \textit{Bank-county Controls}_{ij} + \delta_i + \eta_j + \epsilon_{ij}, \end{aligned} \tag{7}$$

where subscripts i and j denote banks and counties, respectively; β is a coefficient vector of the interaction term and is the key variable of interest; $Inform_{ij}$ is the informativeness variable at the bank-county level; HHI_j is the measure of credit market competitiveness at the county level, and its stand-alone base coefficient is absorbed in the county fixed effects; δ_i and η_j are vectors of bank- and county-fixed effect coefficients, respectively; and ϵ_{ij} is the error term. $\Delta JumboAR_{ij}$ is the change in count-based (or volume-based) jumbo loan approval rate (AR)

[16] I also compute the HHI using market shares based on jumbo loan volumes, and obtain similar results.

of bank i in county j. In the specification, I also control for changes in bank-county level characteristics such as the applicant income, the loan-to-income (LTI) ratio, the minority fraction, and the female fraction. The applicant income and the LTI ratio are changes in averages across all borrowers that submit applications to bank i in county j.

Panel B of Table 12 presents the results of the cross-sectional specification at the bank-county level. Columns 1-2 show the specifications with count-based AR as the dependent variable. Column 1 shows that the coefficient of the informativeness variable (measured by log of the number of jumbo loans issued) is negative and significant, and the coefficient of the interaction term is positive and significant. Column 2 shows that the result is robust to the inclusion of borrower controls. Columns 3-4 use the alternative volume-based AR as the dependent variable and the results are very similar, both economically and statistically.[17] Overall, the findings indicate that not only do less informed lenders increase their approval rates to jumbo borrowers, but the magnitude of this effect increases with the degree of local credit market competition (measured by county-level HHI).

These results imply that informativeness and competition both play a role in affecting banks' lending strategy. Less informed lenders extend their lending to compete for borrowers and market shares, and they lend more aggressively in the counties where the jumbo credit market is more competitive. These findings are consistent with the view that lending experience gives banks market power over their borrowers (Degryse and Ongena (2005)), which they can use to create adverse selection problems for competitor lenders (Dell'Ariccia (2001); and Agarwal and Hauswald (2010)).

5.1.3 Lender jumbo loan specialty

In addition to lenders' informativeness that captures the absolute heterogeneity in information advantage across lenders, I then exploit the jumbo loan specialty that focuses on relative mortgage concentration across lenders. It is possible that some small banks concentrate more

[17] I furthermore test the robustness to the use of alternative measure of informativeness (i.e., loan volume-based measure) for both count- and volume-based approval rates. The results are available upon request.

on jumbo loans relative to their conforming loan businesses, even though they may issue less jumbo loan credit in terms of the absolute quantity.

I focus on the variation in banks' jumbo loan specialty for two major reasons. First, since jumbo loans are information-intensive, lenders with jumbo loan specialty have information advantage over their competitors, which provides incumbents with an advantage over new lenders and thereby limits the number of competitors a market can sustain in equilibrium. Second, as noted in Dell'Ariccia, Friedman, and Marquez (1999), the information advantage of some lenders creates adverse selection problems to their competitors and it represents an entry barrier. Taken together, given a change in jumbo loan share, banks can use their specialty in jumbo loan segment to strategically compete with their competitors and affect local market structures by extending or reducing mortgage credit.

I measure jumbo loan specialty using the ratio of number (or volume) of jumbo loans issued by a lender to a county over the number (or volume) of nonjumbo loans issued by the lender to the county, in the year of 2005. I then analyze whether the extent to which lenders concentrated on their jumbo mortgage lending before the CLL change would have affected their lending strategy after the CLL change when the overall jumbo share of the residential mortgage market declined.

Specifically, I estimate the following first-difference cross-sectional specification:

$$\begin{aligned}\Delta JumboAR_{ij} =& \beta \cdot Specialty_{ij} \cdot HHI_j + \gamma \cdot Specialty_{ij} \\ &+ \zeta \cdot \Delta Bank\text{-}county\ Controls_{ij} + \delta_i + \eta_j + \epsilon_{ij},\end{aligned} \tag{8}$$

where subscripts i and j denote banks and counties, respectively; $\Delta JumboAR_{ij}$ is the change (from pre-2006 to post-2006 period) in count-based (or volume-based) jumbo loan approval rate (AR) of bank i in county j ; $Specialty_{ij}$ is the jumbo loan specialty variable that is defined above at the bank-county level; HHI_j is the measure of credit market competitiveness at the county level which is defined as in Equation (7); δ_i and η_j are vectors of bank- and county-fixed effect coefficients, respectively; and ϵ_{ij} is the error term.

Panel C of Table 12 presents the results of Equation (8). Columns 1-2 (3-4) show the specifications with the count- (volume-) based AR as the dependent variable. Column 1 shows that the coefficient of the count-based jumbo loan specialty variable and the coefficient of its interaction term with competition measure HHI are both negative and significant. Column 2 shows that the result is robust to the inclusion of borrower controls. Columns 3-4 show that the results are robust to the alternative volume-based AR as the dependent variable.[18]

Overall, the findings indicate that: (i) Lenders that have less expertise in jumbo loans increase their jumbo credit supply to local borrowers, which is consistent with the competition channel that they strategically increase lending to create the adverse selection problem for their competitors; (ii) the magnitude of this effect decreases in the degree of credit market competition at the county level (measured by HHI), which suggests that asymmetric information can determine credit market structure and thus limit the number of competitors a market can sustain in equilibrium.

5.2 Heterogeneous borrowers

In this subsection, I examine whether lenders' responses to the CLL change are different across categories of borrowers. Since credit market competition and information asymmetry contribute to determine lenders' responses to the reduction of jumbo loan share across geographical areas, lenders may extend their jumbo credit across different types of borrowers. This may be particularly the case if certain types of borrowers are rationed out when the competition between lenders is less intense.

I first exploit the variation of jumbo loan credit growth across borrower quality. Specifically, I use the loan-to-income (LTI) ratio to proxy for the borrower quality since it provides important hard information in determining a borrower's overall quality (see, e.g., Demyanyk

[18] I furthermore test the robustness to the use of alternative measure of jumbo specialty (i.e., loan volume-based measure) for both count- and volume-based approval rates. The results are available upon request.

and Van Hemert (2011); Keys, Seru, and Vig (2012)). The LTI ratio is defined as the ratio of the total amount of jumbo mortgage over the reported applicant income in the HMDA data.[19] I then divide the mortgage origination sample into two groups based on borrower LTI ratios: low quality (LTI ratio above median) and high quality (LTI ratio below median). To examine the heterogeneity in LTI ratios, I run the baseline specification in Equation (1) for the two groups separately.

[Table 13 inserted here]

Panel A of Table 13 reports the results for the high LTI ratio (columns 1-4) and the low LTI ratio (columns 5-8) groups. In Panel A, the coefficient of the interaction variable is negative and significant; in contrast, the coefficient of the interaction term in Panel B are not only less significant but also smaller in magnitude. These results show that after the CLL increase the jumbo mortgage credit growth is higher for the high LTI ratio group. When lenders are looking for opportunities to extend their market shares in a competitive lending environment, they tend to provide more credit to risky jumbo loan borrowers who may have been rationed out in a less competitive lending environment.

I then analyze whether the extent to which banks expand their lending after the CLL change vary across different loan purposes. Anecdotal evidence suggests that it is easier to shop a refinance than a purchase, in part because of the right of rescission under the Truth in Lending Act that protects borrowers, and in part because many lenders are prepared to assume full responsibility for settlement costs which reduces the burden on borrowers.

Other than the above factors, home-purchase loans and refinancing loans may differ from the lender's perspective. For example, it is likely that some borrowers of home-purchase loans are new to the credit market or have been rejected by another lender, which implies higher information-gathering cost or higher risk. In contrast, some refinancing loan borrowers have

[19] Some previous studies have pointed out that the applicants' income are upward biased (e.g., Mian and Sufi (2016)). In computing LTI ratio using the reported applicant income from HMDA data I implicitly assume that the income information of jumbo loan borrowers across geographic areas and across different categories is inflated to a similar extent.

set up a reliable repayment record and thereby are easier to enter a new mortgage with the same or a new lender. Consistent with this adverse selection channel, I expect to see a strong effect of the CLL change in low-income areas where the competition level is higher after the CLL increase.

Panel B of Table 13 runs the baseline regression in Equation (1) for refinancing mortgage applications (columns 1-4) and home-purchase loan applications (columns 5-8). In line with expectations, the results show that the jumbo mortgage credit growth is higher for the refinancing mortgage applications than for the ones with the home-purchase purpose.

6 Concluding Remarks

In this paper, I analyze the strategic response of lenders facing an exogenous reduction of the jumbo share of local mortgage markets, by exploiting the change in uniform conforming loan limit as the identification strategy. My results establish that, when the local jumbo share is reduced, lenders expand credit to jumbo loan borrowers and compete more aggressively to defend market share. Utilizing rate spread data from HMDA, I also show that banks lower the interest rates of jumbo mortgages especially in areas where the credit market competition is tougher. Furthermore, a larger increase of jumbo approval rate is associated with a relatively poorer future loan performance. My results are consistent with the competition channel that banks give out more jumbo credit without carefully screening borrowers. The effects are especially pronounced in low-income areas where lenders have stronger incentive to defend market share relative to efficiently price the loan. Overall, this paper suggests an unintended consequence of the uniform federal pricing policy that lenders' incentives can be distorted across regions which can further lead to inefficiency of local risk pricing and credit allocation.

Furthermore, on the lender side, smaller banks and banks that are less informed of the local market and that are less specialized in jumbo lending tend to lend more aggressively by expanding credit supply to local borrowers, and the credit expansion grows with competition level of local credit markets. On the borrower side, risky borrowers, i.e., those with higher LTI ratios, and refinancing loans are provided with more credit. In short, my results suggest that lending experience gives banks market power over their borrowers (Degryse and Ongena (2005)), which they can use to create adverse selection problems for competitor lenders (Dell'Ariccia (2001); and Agarwal and Hauswald (2010)).

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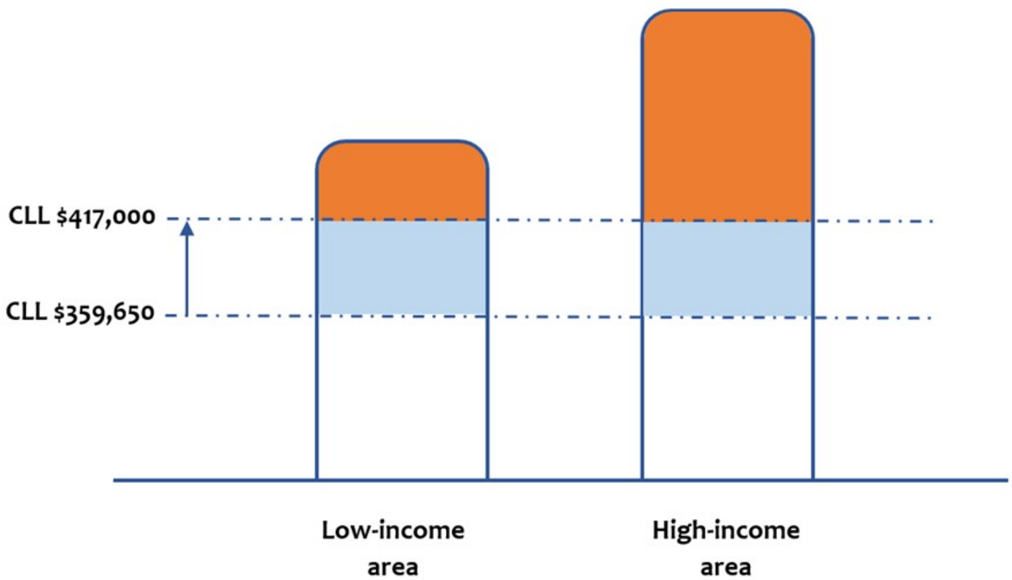


Figure 1: **The effects of the change in conforming loan limit: low-income vs. high-income areas**
This figure shows the effects of the change in the conforming loan limit (CLL) on low-income and high-income areas. At the beginning of 2006, the nationwide CLL increased from $359,650 to $417,000. Each bar indicates the mortgage market structure, from the smallest mortgages at the bottom to the largest ones on the top. The blue area plus the red area in each bar indicate the jumbo mortgages in the area above the old CLL. The red area in each bar indicates the jumbo mortgages in the area above the new CLL.

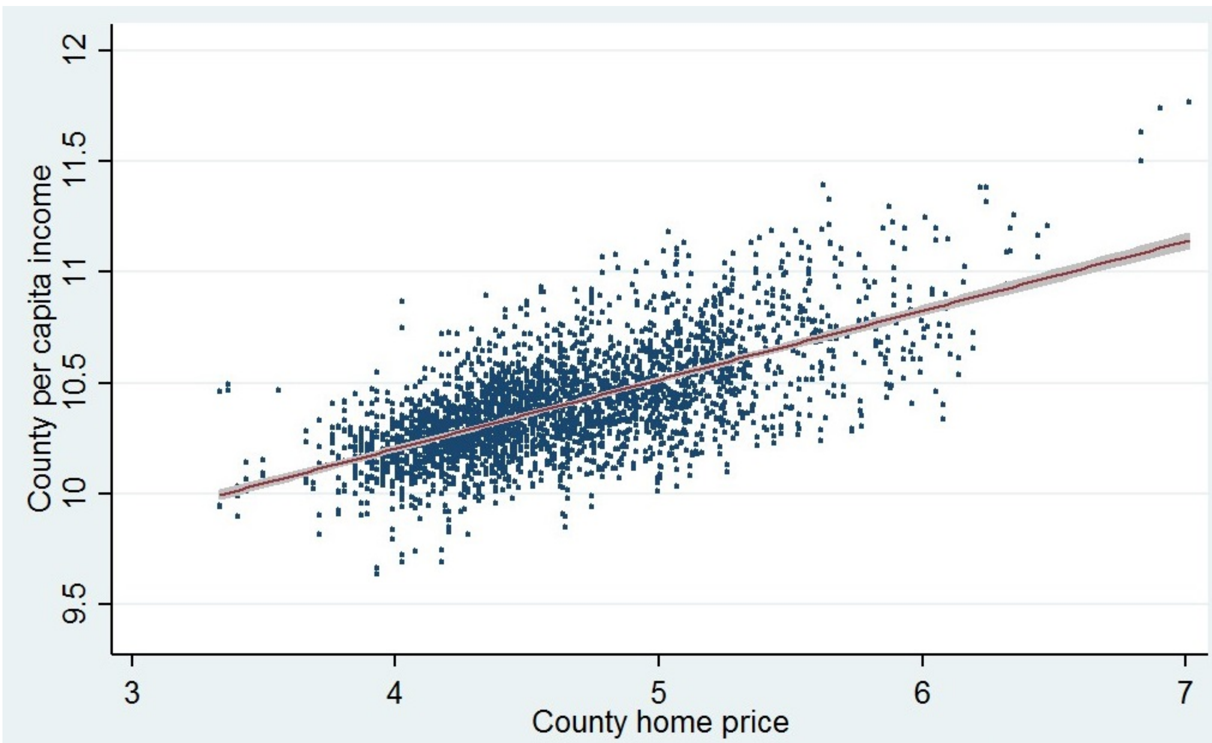
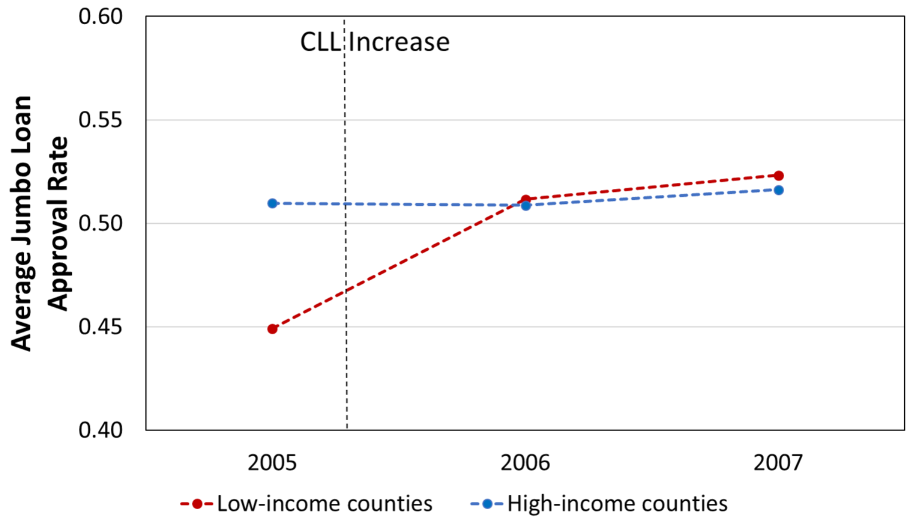


Figure 2: **Correlation of county income and county home price**
This figure plots the scattered dots and the fitted line of county income and county home price. County income is the logarithm of county per capita income obtained from the Bureau of Economic Analysis (BEA). County home price is the logarithm of the median price per square foot obtained from Zillow.com. The solid line is the fitted line of the scattered dots and the shaded area is 95% confidence interval of the fitted line.

A. Jumbo loan approval rate



B. Non-jumbo loan approval rate

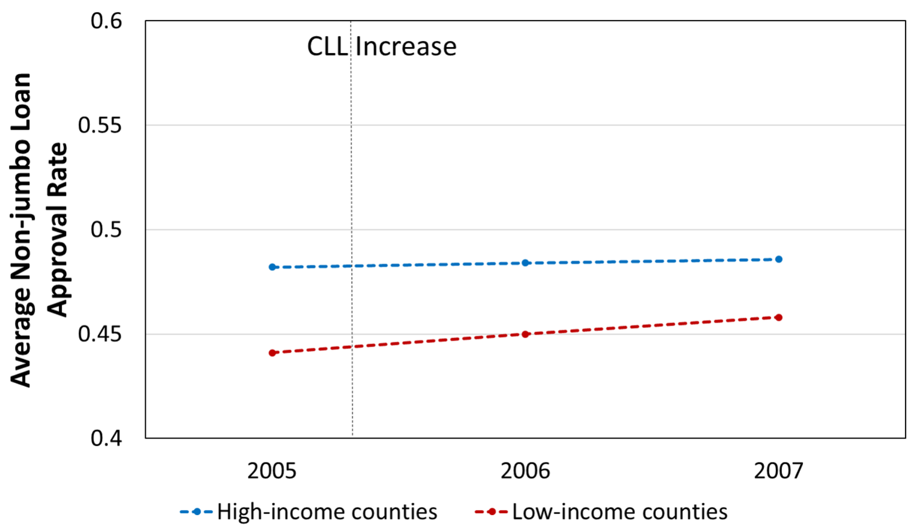


Figure 3: **Average jumbo loan approval rates for low-income and high-income counties**

Panel A of this figure plots the average jumbo loan approval rates for low-income and high-income counties before and after the CLL increases at the beginning of 2006. Panel B of this figure plots the average non-jumbo loan approval rates for low-income and high-income counties before and after the CLL increases at the beginning of 2006. In both panels, red dashed line plots the average approval rates for low-income counties; blue dashed line plots the average approval rates for high-income counties. A county is classified as low-income (high-income) if its per capita income is below (above) the median value of all county incomes in 2005.

Table 1: **Summary statistics**

This table presents summary statistics of all mortgage, bank, and socio-economic variables at the county level before and after the increase of conforming loan limit (CLL) in 2006. Mortgage application data are from HMDA loan applications and originations from 2005 to 2007. County-level socio-economic variables are based on data from the Bureau of Economic Analysis (BEA). Bank-related data are obtained from the Reports of Condition and Income for commercial banks ("Call Reports"). The CLL increased from \$359,650 in 2005 to \$417,000 in 2006. The Pre-06 period refers to the entire year of 2005, and the Post-06 period refers to two entire years of 2006 and 2007. High (low) income counties are classified as counties with higher-(lower-)than-median county-level median income in the given year. All variables are defined in Appendix A.

	High Income Counties				Low Income Counties			
	Pre-06 Limit Change		Post-06 Limit Change		Pre-06 Limit Change		Post-06 Limit Change	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Dependent variables								
Jumbo Acceptance Rate (Count)	0.509	0.191	0.508	0.181	0.456	0.262	0.519	0.287
Jumbo Acceptance Rate (Volume)	0.532	0.197	0.533	0.195	0.466	0.274	0.535	0.297
Non-jumbo Accept. Rate (Count)	0.487	0.065	0.490	0.053	0.448	0.069	0.463	0.065
Non-jumbo Accept. Rate (Vol.)	0.482	0.069	0.484	0.057	0.441	0.070	0.450	0.065
Mortgage application								
No. of Loan Applications	24146	66247	23291	61251	3799	13424	3201	12008
No. of Loans Issued	10646	28816	9760	24580	1573	5734	1298	4712
No. of Jumbo Loan Applications	2672	15408	2064	12463	146	1809	96	1228
No. of Jumbo Loans Accepted	1371	7878	996	5927	73	911	44	545
No. of Jumbo Loans Retained	379	1983	287	1557	21	204	13	116
County Median Income ('000)	35.018	7.647	36.672	8.935	24.849	2.817	25.588	2.949
County Income Growth (%)	4.746	5.145	5.287	7.688	3.367	3.931	2.556	5.287
Log(Applicant Income)	4.088	0.257	4.162	0.268	3.852	0.178	3.909	0.187
Loan-to-income Ratio	2.018	0.463	2.008	0.450	1.841	0.359	1.789	0.351
Minority Applicant Fraction	0.068	0.083	0.074	0.087	0.088	0.112	0.083	0.111
Female Applicant Fraction	0.246	0.046	0.248	0.043	0.254	0.044	0.254	0.052
Bank Controls								
Log(Assets)	15.420	0.888	15.680	0.908	15.781	0.738	16.157	0.739
Leverage	0.105	0.007	0.103	0.005	0.105	0.009	0.102	0.008
Accounting Profits	0.695	0.035	0.696	0.029	0.693	0.041	0.695	0.032
Liquidity	0.168	0.033	0.165	0.027	0.163	0.041	0.159	0.035
Loans/Assets	0.695	0.035	0.696	0.029	0.692	0.042	0.694	0.034
Deposits/Assets	0.692	0.051	0.709	0.037	0.667	0.062	0.687	0.054
Deposit Cost	0.041	0.006	0.037	0.005	0.041	0.007	0.036	0.005
Letters of credit/Assets	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000
Unused Loan Cmt/Assets	0.548	0.273	0.500	0.326	0.609	0.247	0.557	0.212
C&I Loans/Assets	0.116	0.021	0.109	0.015	0.116	0.021	0.105	0.016
Real Estate Loans/Assets	0.386	0.044	0.383	0.039	0.378	0.044	0.374	0.036
Securitization Ratio	0.685	0.091	0.662	0.081	0.620	0.113	0.597	0.108

Table 2: **Regional variation in lender responses to uniform CLL increase**

This table examines the changes in the approval rates for jumbo mortgages at the county-year level before and after the conforming loan limit increased from $359,650 to $417,000 at the beginning of 2006. The sample period is from 2005 to 2007. The dependent variables in columns 1-4 (5-8) are jumbo loan approval rates based on total number (volume) of jumbo loans at the county level. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. *HPI Growth* is the county-level housing price index growth rate, and *HPI Growth Lag* is its lagged value. Columns 2, 4, 6, and 8 include borrower, bank, and county controls. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
County Income*Post	-0.006***	-0.004***			-0.006***	-0.005***		
	(0.001)	(0.001)			(0.001)	(0.001)		
County Income	0.013***	0.012***			0.014***	0.014***		
	(0.004)	(0.004)			(0.004)	(0.004)		
Log(County Income)*Post			-0.188***	-0.151***			-0.205***	-0.170***
			(0.024)	(0.027)			(0.025)	(0.028)
Log(County Income)			0.436***	0.453***			0.480***	0.530***
			(0.143)	(0.157)			(0.143)	(0.158)
HPI Growth		0.306***		0.299***		0.314***		0.307***
		(0.069)		(0.069)		(0.073)		(0.073)
HPI Growth Lag		0.285***		0.261***		0.287***		0.260***
		(0.082)		(0.082)		(0.086)		(0.086)
Observations	7,506	7,482	7,506	7,482	7,506	7,482	7,506	7,482
Borrower Controls		Yes		Yes		Yes		Yes
County Controls		Yes		Yes		Yes		Yes
Bank Controls		Yes		Yes		Yes		Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.138	0.156	0.140	0.157	0.136	0.161	0.139	0.162

Table 3: **Competition channel and the increase in jumbo approval rate**

This table examines how credit market competition changes the approval rates for jumbo mortgages at the county level before and after the increase of conforming loan limit at the beginning of 2006. The dataset is at the county-year level from 2005 to 2007. Panel A adds *Jumbo HHI* as a measure of jumbo lenders competition to test its relation with jumbo loan approval rates. *Jumbo HHI count (volume)* is the Herfindahl-Hirschman index (HHI) which is defined as the sum of the squared count (volume) fractions of issued jumbo loans by each lender in a given county over all issued jumbo loans in the given county. Panel B only focuses on high income counties which are above the median value of county per capita income, and the high- and low-competition counties are classified by the median *Jumbo HHI (count)* measure across the high income counties. In both panels, the dependent variables in columns 1-2 (3-4) are jumbo loan approval rates based on total number (volume) of jumbo loans at the county level. *Log(County Income)* is the logarithm of county per capita income obtained from the Bureau of Economic Analysis (BEA). The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. All regressions control for borrower, county, and bank characteristics. Borrower controls include applicant income and loan-to-income ratio. County controls include county income growth, minority fraction, and female fraction. Bank controls include total assets, leverage, accounting profits, liquidity, deposit ratio, deposit costs, letters of credit, C&I loans, and real estate loans. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Competition measures of jumbo loan lenders: jumbo HHI

	(1)	(2)	(3)	(4)
Dep. Var.	Jumbo AR (Count)		Jumbo AR (Volume)	
Log(County Income)*Post	-0.159***	-0.160***	-0.184***	-0.183***
	(0.021)	(0.021)	(0.022)	(0.022)
Log(County Income)	0.431***	0.430***	0.530***	0.520***
	(0.102)	(0.103)	(0.106)	(0.107)
Jumbo HHI (Count)	-0.173***		-0.195***	
	(0.024)		(0.026)	
Jumbo HHI (Volume)		-0.149***		-0.095***
		(0.023)		(0.025)
Observations	6,562	6,562	6,562	6,562
Borrower Controls	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R2	0.335	0.330	0.320	0.302

Table 3: **(Cont.) Competition channel and the increase in jumbo approval rate**

Panel B. Subsample analysis: high income counties

	(1)	(2)	(3)	(4)
Dep. Var.	Jumbo AR (Count)		Jumbo AR (Volume)	
	Low Competition	High Competition	Low Competition	High Competition
Log(County Income)*Post	-0.240	-0.030***	-0.248	-0.038***
	(0.165)	(0.009)	(0.168)	(0.011)
Log(County Income)	0.912**	0.027	0.955**	0.148**
	(0.371)	(0.056)	(0.374)	(0.065)
Observations	1,553	1,816	1,553	1,816
Borrower Controls	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R2	0.177	0.638	0.173	0.586

Table 4: **Competition channel and jumbo mortgage price**

This table examines the changes in the rate spread for jumbo mortgages at the county level before and after the conforming loan limit increased from $359,650 to $417,000 at the beginning of 2006. The dataset is at the county-year level from 2005 to 2007. The dependent variable in columns 1-4 (5-8) is the median (mean) value of jumbo mortgage rate spread in a county in a given year. The rate spread data is obtained from the HMDA database. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. *HPI Growth* is the county-level housing price index growth rate, and *HPI Growth Lag* is its lagged value. Columns 2, 4, 6, and 8 include borrower, bank, and county controls. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Median Jumbo Rate Spread				Mean Jumbo Rate Spread			
County Income*Post	0.005**	0.007**			0.005**	0.006**		
	(0.002)	(0.003)			(0.002)	(0.002)		
County Income	-0.001	-0.006*			0.001	-0.006**		
	(0.002)	(0.003)			(0.002)	(0.003)		
Log(County Income)*Post			0.231**	0.274**			0.247**	0.246**
			(0.110)	(0.121)			(0.105)	(0.112)
Log(County Income)			-0.032	-0.340***			0.072	-0.287**
			(0.089)	(0.126)			(0.087)	(0.119)
HPI Growth		-0.380		-0.379		-0.531*		-0.526*
		(0.297)		(0.297)		(0.290)		(0.290)
HPI Growth Lag		0.684**		0.669**		0.244		0.244
		(0.337)		(0.337)		(0.358)		(0.357)
Observations	3,713	3,689	3,713	3,689	3,713	3,689	3,713	3,689
Borrower Controls		Yes		Yes		Yes		Yes
County Controls		Yes		Yes		Yes		Yes
Bank Controls		Yes		Yes		Yes		Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.075	0.086	0.076	0.086	0.052	0.069	0.053	0.07

Table 5: **Jumbo approval rate increase and loan performance**

This table examines the impact of the increased approval rate of jumbo loans on bank loan performance. The dataset is at the bank-year level from 2005 to 2008. Panel A uses the full sample. Panel B uses a subsample of banks with intensive exposure to jumbo mortgage lending. This subsample includes banks with the ratio of jumbo mortgage origination volumes/total mortgage origination volumes (from the HMDA data) above its median value. In both panels, the dependent variables in columns 1, 2, 3, and 4 are *NPL/family loans* (1-4 family loans 90 or more days past due plus loans no longer accruing interest/total 1-4 family loans), *NPL/family loans only based on first liens*, *family charge-offs/family loans* (1-4 family loans charge-offs/ total 1-4 family loans), and *family charge-offs/loan charge-offs* (1-4 family loans charge-offs/ total loans charge-offs), respectively. *Jumbo AR increase* is the percentage change of the number-based approval rate in this year relative to the previous year of a bank in a given year. All columns include bank controls. All regression controls are defined in Appendix A. All regressions include bank fixed effects and year fixed effects. Standard errors in parentheses are clustered at the bank level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Full sample

Dep. Var.	(1) NPL/ Family loans	(2) NPL/Family loans (First lien only)	(3) Family Charge-offs/ Family loans	(4) Family Charge-offs/ Loan charge-offs
Jumbo AR increase (Volume)	0.0004**	0.0004**	0.0000	-0.0015
	(0.000)	(0.000)	(0.000)	(0.002)
Observations	9,546	9,544	9,546	8,831
Bank Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R2	0.0565	0.0449	0.0166	0.0138

Panel B. Intensive jumbo loan lenders

Dep. Var.	(1) NPL/ Family loans	(2) NPL/Family loans (First lien only)	(3) Family Charge-offs/ Family loans	(4) Family Charge-offs/ Loan charge-offs
Jumbo AR increase (Volume)	0.0013**	0.0014**	0.0002*	0.0081***
	(0.000)	(0.001)	(0.000)	(0.003)
Observations	7,012	7,010	7,012	6,362
Bank Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R2	0.0485	0.0365	0.00894	0.00765

Table 6: **Regional variation in lender responses to uniform CLL increase: within-bank tests**

This table runs within-bank tests and examines the changes in the approval rates for jumbo mortgages at the county-year level before and after the conforming loan limit increased from $359,650 to $417,000 at the beginning of 2006. The sample period is from 2005 to 2007. The dependent variables in columns 1-4 (5-8) are jumbo loan approval rates based on total number (volume) of jumbo loans in the range of $417,000 to $600,000 at the bank-county level. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. *HPI Growth* is the county-level housing price index growth rate, and *HPI Growth Lag* is its lagged value. Columns 2, 3, 4, 6, 7, and 8 include borrower, bank, and county controls. Columns 1, 3, 4, 5, 7, and 8 include county, year, and bank-year fixed effects. Columns 2 and 6 include county, year, and bank fixed effects. All regression controls are defined in Appendix A. A Standard errors in parentheses are double clustered at both the county and bank levels. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
County Income*Post	-0.001**	-0.002***	-0.001**	-0.001**	-0.001***	-0.002***	-0.001**	-0.001**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
County Income	0.003***	0.008	0.007***	0.007	0.003***	0.008	0.007***	0.007
	(0.001)	(0.051)	(0.003)	(3.970)	(0.001)	(0.996)	(0.003)	(1.111)
HPI Growth			0.185***	0.153***			0.185***	0.153
			(0.049)	(0.023)			(0.049)	(0.319)
HPI Growth Lag			0.082*	0.096			0.079*	0.093
			(0.045)	(0.097)			(0.045)	(0.068)
Observations	235,831	49,577	50,349	48,452	235,831	49,577	50,349	48,452
Borrower Controls		Yes	Yes	Yes		Yes	Yes	Yes
County Controls		Yes	Yes	Yes		Yes	Yes	Yes
Bank Controls			Yes				Yes	
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE			Yes				Yes	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Year FE	Yes	Yes		Yes	Yes	Yes		Yes
Adj. R2	0.390	0.262	0.243	0.260	0.390	0.262	0.243	0.260

Table 7: **Alternative explanations: borrower credit and securitization ratio improvements**

This table examines alternative explanations of the impacts of the CLL change on the approval rates for jumbo mortgages at the county-year level. The sample period is from 2005 to 2007. The dependent variables in columns 1-6 are jumbo loan approval rates based on total number of jumbo loans at the county level. In columns 1-4, I calculate approval rates in each county for jumbo loan applications in 2005 based on a subset of borrowers who are BOTH above the lowest income of 2006 applicants *AND* below the highest LTI ratio of 2006 applicants, with income adjusted by the inflation rate. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. Columns 5-6 further control for county-level securitization ratio which is defined as the weighted average securitization ratio of banks in a given county (weighted by bank market shares), and for each bank the securitization ratio is computed as the total volume of securitized mortgages divided by the total volume of issued mortgages. Other regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Jumbo AR (Count)					
	Subsample_LTI_Income				Control for Sec ratio	
County Income*Post	-0.004***	-0.003***			-0.004***	
	(0.001)	(0.001)			(0.001)	
County Income	0.008*	0.006*			0.012***	
	(0.004)	(0.004)			(0.004)	
Log(County Income)*Post			-0.147***	-0.122***		-0.151***
			(0.023)	(0.026)		(0.027)
Log(County Income)			0.243	0.191		0.453***
			(0.162)	(0.149)		(0.157)
Securitization Ratio (Cty Mean)					-0.625***	-0.631***
					(0.113)	(0.112)
Observations	6,903	6,879	6,903	6,879	7,482	7,482
Borrower Controls		Yes		Yes	Yes	Yes
Bank Controls		Yes		Yes	Yes	Yes
County Controls		Yes		Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.180	0.185	0.181	0.186	0.156	0.157

Table 8: **Reduction of jumbo share and approval rate increase: difference-in-difference analysis and propensity score matching**

Panel A presents summary statistics of county-level and loan-level key variables as of end-2007 in matched treated (counties that are determined as "high-cost" areas by the Federal Housing Finance Agency (FHFA) in 2008 and matched with control counties based on the listed observables) and matched control (counties that are not determined as "high-cost" areas and matched with treated counties based on the listed observables) counties. Panel B reports estimates of panel regressions at the county-year level in columns 1-6, where the dependent variables are the number-(volume-)based jumbo loan approval rates in columns 1-3 (4-6). Columns 7-9 report the regressions at the loan-year level, where the dependent variable is the *Accept* dummy that takes the value of 1 if the jumbo mortgage application is accepted by the bank and 0 otherwise. The sample period is from 2007 to 2008. The indicator variable *Post* takes the value 1 for the year of 2008 and 0 for the year of 2007. In columns 1-6, *Treated* is a dummy variable that takes the value of 1 if the county is determined as a "high-cost" county in 2008 and 0 otherwise. The included control variables are listed in Panel A and defined in Appendix A. All regressions include county and year fixed effects. Standard errors in parentheses are clustered at the county level. In columns 7-9, Treated is a dummy variable that takes the value of 1 if the jumbo mortgage is submitted in a "high-cost" county that is determined in 2008 and 0 otherwise. The included control variables are listed in Panel A and defined in Appendix A. All regressions include county, bank, and year fixed effects. Standard errors in parentheses are double clustered by bank and county. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Summary statistics for treated and control counties/mortgages

	County-level			Loan-level	
	Control Mean	Treated Mean		Control Mean	Treated Mean
Borrower Controls					
Log(Applicant Income)	4.381	4.743	Log(Applicant Income)	5.650	5.327
LTI Ratio	2.910	2.849	LTI Ratio	3.760	3.442
Minority Fraction	0.141	0.148	Minority Dummy	0.129	0.192
Female Fraction	0.270	0.270	Female Dummy	0.174	0.224
Lender Controls					
Log(Assets)	16.171	15.509	Log(Assets)	19.777	19.058
Leverage	0.108	0.109	Leverage	0.091	0.092
Accounting Profits	0.691	0.685	Accounting Profits	0.514	0.610
Liquidity	0.152	0.164	Liquidity	0.124	0.150
Loans/Assets	0.691	0.685	Loans/Assets	0.514	0.610
Deposits/Assets	0.687	0.705	Deposits/Assets	0.626	0.674
Deposit Cost	0.035	0.038	Deposit Cost	0.037	0.035
Letters of credit/Assets	0.001	0.001	Letters of credit/Assets	0.003	0.002
Unused Loan Cmt/Assets	0.429	0.418	Unused Loan Cmt/Assets	0.378	0.499
C&I Loans/Assets	0.114	0.110	C&I Loans/Assets	0.096	0.112
Real Estate Loans/Assets	0.363	0.385	Real Estate Loans/Assets	0.244	0.307
Securitization Ratio	0.658	0.636	Securitization Ratio	0.642	0.581
			BHC Dummy	0.996	0.937
County Controls					
County Income Mean ('000)	38.365	54.282	County Income Mean ('000)	40.306	49.010
County Income Growth (%)	4.705	4.616	County Income Growth (%)	3.768	4.240
No. of matched units	20	76	No. of matched units	7,334	305,993

Table 8: **(Cont.) Reduction of jumbo share and approval rate increase: difference-in-difference analysis and propensity score matching**

Panel B. High cost areas and jumbo mortgage approval rates

	County-level						Loan-level		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	Jumbo AR (Count)			Jumbo AR (Volume)			Accept		
Treated*Post	0.076**	0.087**	0.129**	0.106***	0.123**	0.282**	0.045**	0.041**	0.024**
	(0.028)	(0.036)	(0.055)	(0.027)	(0.053)	(0.108)	(0.020)	(0.019)	(0.012)
Observations	154	154	154	154	154	154	383,925	383,925	383,925
Borrower Controls		Yes	Yes		Yes	Yes		Yes	Yes
Bank Controls			Yes			Yes			Yes
County Controls			Yes			Yes			Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE							Yes	Yes	Yes
Adj. R2	0.219	0.251	0.225	0.260	0.277	0.344	0.111	0.112	0.113

Table 9: **Alternative explanations: home price expectation and the demand channel**

This table examines changes in the jumbo mortgage credit supply before and after the increase of conforming loan limit (CLL) in 2006 and runs baseline regressions on different subsamples to test the home price expectation hypothesis and the jumbo mortgage borrower income (demand) hypothesis. The dataset is at the county-year level from 2005 to 2007. Panel A reports the regression estimates on high land supply elasticity subsample, i.e., counties that overlap with metro statistical areas (MSAs) with the land supply elasticities higher than 2.21 from Table VI in Saiz (2010). Panel B (C) reports the regression estimates on low income (growth) subsample that comprises counties with per capita income (growth rate) lower than its median value. The dependent variable in Panels A, B, and C columns 1-4 (5-8) is the number-(volume-)based jumbo mortgage approval rate. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. Columns 3, 4, 7, and 8 include borrower, bank, and county controls. Borrower controls include applicant income and loan-to-income ratio. County controls include county income growth, minority fraction, and female fraction. Bank controls include total assets, leverage, accounting profits, liquidity, deposit ratio, deposit costs, letters of credit, C&I loans, and real estate loans. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Land supply elasticity and jumbo mortgage approval rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High Supply Elasticity				High Supply Elasticity			
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
County Income*Post	-0.004***		-0.003**		-0.004***		-0.003**	
	(0.001)		(0.001)		(0.001)		(0.001)	
County Income	0.005		0.001		0.003		0.002	
	(0.006)		(0.008)		(0.007)		(0.008)	
Log(County Income)*Post		-0.135***		-0.119***		-0.143***		-0.140***
		(0.040)		(0.044)		(0.046)		(0.049)
Log(County Income)		0.216		-0.012		0.126		0.117
		(0.274)		(0.297)		(0.334)		(0.353)
Observations	465	465	465	465	465	465	465	465
Borrower Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.218	0.222	0.211	0.215	0.262	0.265	0.248	0.252

Table 9: **(Cont.) Alternative explanations: home price expectation and the demand channel**

Panel B. Borrower income and jumbo mortgage approval rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low Income Subsample				Low Income Subsample			
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
County Income*Post	-0.021***		-0.021***		-0.021***		-0.022***	
	(0.005)		(0.005)		(0.005)		(0.005)	
County Income	0.034***		0.030*		0.035***		0.034**	
	(0.013)		(0.016)		(0.013)		(0.016)	
Log(County Income)*Post		-0.444***		-0.448***		-0.447***		-0.455***
		(0.120)		(0.121)		(0.123)		(0.125)
Log(County Income)		0.790**		0.700*		0.818**		0.814**
		(0.312)		(0.385)		(0.319)		(0.385)
Observations	3,323	3,323	3,323	3,323	3,323	3,323	3,323	3,323
Borrower Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.089	0.089	0.094	0.093	0.091	0.09	0.098	0.097

Panel C. Borrower income growth and jumbo mortgage approval rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low Income Growth Subsample				Low Income Growth Subsample			
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
County Income*Post	-0.007***		-0.004**		-0.007***		-0.005***	
	(0.002)		(0.002)		(0.002)		(0.002)	
County Income	0.007*		0.008		0.010**		0.012**	
	(0.004)		(0.005)		(0.005)		(0.005)	
Log(County Income)*Post		-0.212***		-0.128**		-0.225***		-0.147**
		(0.053)		(0.058)		(0.054)		(0.060)
Log(County Income)		0.212		0.194		0.302*		0.319
		(0.174)		(0.204)		(0.177)		(0.200)
Observations	2,681	2,681	2,681	2,681	2,681	2,681	2,681	2,681
Borrower Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.177	0.177	0.202	0.202	0.206	0.206	0.236	0.236

Table 10: **Regional variation in lender responses to uniform CLL increase: a placebo test**

This table compares our baseline results in columns 1 and 4 with similar estimations for an alternative sample period. The results in columns 2 and 5 are based on panel regressions over the period from 2006 to 2007 ("Placebo"). The dependent variable in columns 1-2 (4-5) is the number-(volume-)based jumbo mortgage approval rate. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). In columns 1 and 4 (2 and 5) the indicator variable Post takes the value 1 for two entire years from 2006 to 2007 (2007) and 0 for the year of 2005 (2006). Other regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Columns 36 show p-values of one-sided t-tests to check whether the estimated coefficients based on different sample periods are significantly different.

	(1)	(2)	(3)	(4)	(5)	(6)
			T-test (p-value)			T-test (p-value)
	Jumbo AR (Count)		Baseline	Jumbo AR (Volume)		Baseline
Dep. Var.	Baseline	Placebo (06-07)	>Placebo	Baseline	Placebo (06-07)	>Placebo
County Income*Post	-0.005***	-0.001	0.00	-0.005***	-0.001	0.00
	(0.001)	(0.001)		(0.001)	(0.001)	
County Income	0.015***	0.010		0.016***	0.011	
	(0.004)	(0.008)		(0.004)	(0.008)	
Observations	7,506	4,770		7,506	4,770	
County FE	Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes	
Adj. R2	0.160	0.112		0.156	0.0948	

Table 11: **Regional variation in lender responses to uniform CLL increase: robustness checks**

This table shows robustness tests for our baseline regressions to explain the regional heterogeneity of jumbo loan approval rates after the conforming loan limit (CLL) increased in 2006. It is estimated using baseline regressions and the dataset is at the county-year level from 2005 to 2007. Columns 1 and 5 include a linear time trend that is identical across all counties and drop year fixed effects. Columns 2 and 6 include state-specific time trends that allow each state to have different trends in jumbo loan credit supply and drop year fixed effects. Columns 3 and 7 are based on regressions that exclude the lowest income counties (i.e., bottom quartile). Columns 4 and 8 are based on a sample that excludes extreme approval rates (1% of the distribution on both sides). The dependent variable is number-(volume-)based jumbo loan approval rate in columns 1-4 (5-8). *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. All regressions control for borrower, bank, and county characteristics that are defined in Appendix A. All models include county fixed effects. Columns 3, 4, 7, and 8 also include year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
	Time Trends	State-Time Trends	Excluding lowest income counties	Excluding Extreme AR	Time Trends	State-Time Trends	Excluding lowest income counties	Excluding Extreme AR
County Income*Post	-0.006***	-0.004***	-0.004***	-0.002***	-0.006***	-0.004***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
County Income	0.014***	0.011***	0.013***	0.006***	0.016***	0.012***	0.015***	0.010***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)
Post	0.156***	0.115***			0.180***	0.135***		
	(0.036)	(0.037)			(0.037)	(0.038)		
Year	0.028**				0.021			
	(0.013)				(0.013)			
Observations	7,506	7,506	5,507	4,509	7,506	7,506	5,507	4,509
Time Trends	Yes				Yes			
State-Time Trends		Yes				Yes		
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE			Yes	Yes			Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.151	0.157	0.211	0.346	0.156	0.161	0.210	0.332

Table 12: **Heterogeneity in lenders and jumbo approval rate increase**

This table examines changes in the jumbo mortgage credit supply before and after the increase of conforming loan limit (CLL) in 2006 and runs baseline regressions on different subsamples to examine the heterogeneity of lender size. The dataset is at the county-year level from 2005 to 2007. In Panel A, columns 1-4 (5-8) are based on a subsample that includes jumbo loan applications to small (large) banks. A bank is classified as large if the total assets is above the top one percent cutoff of the assets distribution, and classified as small if it below the top one percent cutoff. The dependent variable in columns 1-4 (5-8) is the number-based jumbo mortgage approval rate calculated using the subsample of small (large) banks. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. Columns 3, 4, 7, and 8 include borrower, bank, and county controls. Borrower controls include applicant income and loan-to-income ratio. County controls include county income growth, minority fraction, and female fraction. Bank controls include total assets, leverage, accounting profits, liquidity, deposit ratio, deposit costs, letters of credit, C&I loans, and real estate loans. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Panels B and C estimate a first-difference cross-sectional regression. The dependent variable in columns 1-2 (3-4) is the change in number-(volume-) based jumbo mortgage approval rate before (i.e., in 2005) and after the CLL increase at the beginning of 2006 (i.e., in 2006 and 2007). In Panel B, *Inform_Num* is defined as the logarithm of the number of jumbo loans that a bank issued in a county in 2005. In Panel C, *Specialty_Num* is defined as the ratio of number of jumbo loans issued by a lender to a county over the number of nonjumbo loans issued by the lender to the county, in the year of 2005. *Jumbo HHI* is the Herfindahl-Hirschman index (HHI) in 2005 computed by summing up the square of each bank's market share in a county, where market share of the bank is defined as the ratio of the number of jumbo loans issued by the bank over the total number of issued jumbo loans by all banks in the given county in 2005. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Lender size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Small Banks' Jumbo AR (Count)				Large Banks' Jumbo AR (Count)			
Log(County Income)*Post	-0.053**		-0.073***		-0.004		-0.045	
	(0.024)		(0.028)		(0.026)		(0.029)	
Log(County Income)	0.068		-0.052		0.217		0.330*	
	(0.125)		(0.169)		(0.167)		(0.194)	
County Income*Post		-0.001**		-0.002**		-0.001		-0.002**
		(0.001)		(0.001)		(0.001)		(0.001)
County Income		0.003		0.001		0.007*		0.009**
		(0.003)		(0.004)		(0.004)		(0.004)
Observations	5,877	5,877	5,877	5,877	5,419	5,419	5,419	5,419
Borrower Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.230	0.229	0.235	0.234	0.139	0.139	0.141	0.141

Table 12: **(Cont.) Heterogeneity in lenders and jumbo approval rate increase**

Panel B. Lender informativeness

	(1)	(2)	(3)	(4)
Dep. Var.	Δ Jumbo AR (Count)		ΔJumbo AR (Volume)	
Inform_Num*Jumbo HHI	0.016***	0.016***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
Inform_Num	-0.094***	-0.095***	-0.094***	-0.095***
	(0.020)	(0.020)	(0.020)	(0.020)
ΔLog(Applicant Income)		-0.051***		-0.058***
		(0.010)		(0.010)
ΔLog(LTI Ratio)		-0.069***		-0.071***
		(0.011)		(0.012)
ΔMinority Fraction		-0.037**		-0.034**
		(0.017)		(0.017)
ΔFemale Fraction		0.002		0.000
		(0.012)		(0.013)
Observations	50,094	49,853	50,094	49,853
Borrower Controls		Yes		Yes
County FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Adj. R2	0.117	0.118	0.111	0.113

Panel C. Lender specialty

	(1)	(2)	(3)	(4)
Dep. Var.	ΔJumbo AR (Count)		ΔJumbo AR (Volume)	
Specialty_Num*Jumbo HHI	-0.017***	-0.018***	-0.017***	-0.017***
	(0.489)	(0.495)	(0.490)	(0.496)
Specialty_Num	-0.197***	-0.202***	-0.199***	-0.204***
	(0.034)	(0.035)	(0.034)	(0.035)
ΔLog(Applicant Income)		-0.046***		-0.052***
		(0.010)		(0.011)
ΔLog(LTI Ratio)		-0.068***		-0.072***
		(0.012)		(0.012)
ΔMinority Fraction		-0.033*		-0.030*
		(0.018)		(0.018)
ΔFemale Fraction		0.009		0.009
		(0.013)		(0.013)
Observations	60,344	60,037	60,344	60,037
Borrower Controls		Yes		Yes
County FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Adj. R2	0.0946	0.0951	0.0927	0.0934

Table 13: **Heterogeneity in borrowers: loan-to-income ratios and loan purposes**

This table examines changes in the jumbo mortgage credit supply before and after the increase of conforming loan limit (CLL) in 2006 and runs baseline regressions on different subsamples to examine the heterogeneity of borrowers' loan-to-income (LTI) ratios. The dataset is at the county-year level from 2005 to 2007. In Panel A, columns 1-4 (5-8) are based on a subsample that includes borrowers with LTI ratios above (below) the median value of LTI ratio. The dependent variable is the number-based jumbo mortgage approval rate calculated using the corresponding subsample. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. In Panel B, columns 1-4 (5-8) are based on a subsample that includes only mortgages with the refinancing purpose (home purchase purpose). The dependent variable is the number-based jumbo mortgage approval rate calculated using the corresponding subsample. In both panels, columns 3, 4, 7, and 8 include borrower, bank, and county controls. Borrower controls include applicant income and loan-to-income ratio. County controls include county income growth, minority fraction, and female fraction. Bank controls include total assets, leverage, accounting profits, liquidity, deposit ratio, deposit costs, letters of credit, C&I loans, and real estate loans. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. LTI ratios of borrowers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Borrowers with high LTI ratios				Borrowers with low LTI ratios			
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Count)			
County Income*Post	-0.006***		-0.005***		-0.001*		-0.001*	
	(0.001)		(0.001)		(0.001)		(0.001)	
County Income	0.012***		0.010*		0.002		0.003	
	(0.004)		(0.005)		(0.003)		(0.004)	
Log(County Income)*Post		-0.189***		-0.171***		-0.045*		-0.051*
		(0.025)		(0.029)		(0.024)		(0.027)
Log(County Income)		0.347**		0.233		-0.040		0.108
		(0.144)		(0.217)		(0.128)		(0.172)
Observations	6,705	6,705	6,705	6,705	6,467	6,467	6,467	6,467
Borrower Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.141	0.142	0.154	0.156	0.249	0.250	0.257	0.257

Table 13: **(Cont.) Heterogeneity in borrowers: loan-to-income ratios and loan purposes**

Panel B. Borrowers with different loan purposes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Refinancing borrowers				Home purchase borrowers			
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Count)			
County Income*Post	-0.005***		-0.005***		0.000		-0.001	
	(0.001)		(0.001)		(0.001)		(0.001)	
County Income	0.017***		0.015***		-0.005		0.000	
	(0.004)		(0.004)		(0.004)		(0.004)	
Log(County Income)*Post		-0.150***		-0.134***		-0.020		-0.025
		(0.024)		(0.026)		(0.025)		(0.027)
Log(County Income)		0.574***		0.547***		-0.177		0.049
		(0.137)		(0.166)		(0.163)		(0.173)
Observations	6,862	6,862	6,862	6,862	5,985	5,985	5,985	5,985
Borrower Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.190	0.191	0.195	0.196	0.112	0.112	0.118	0.118

Appendix

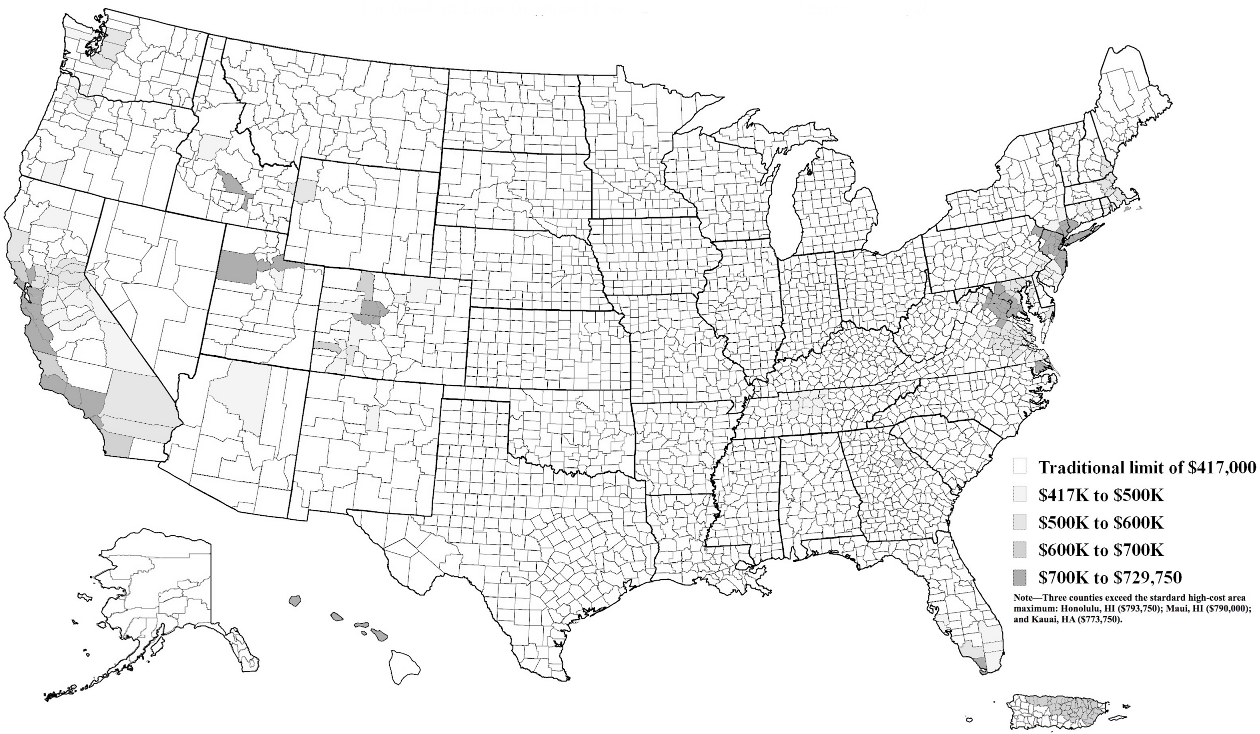


Figure A1: **The map of the high-cost areas in 2008**
This figure shows the map of the counties that are determined as the high-cost areas by the Federal Housing Finance Agency (FHFA). Counties that are marked in darker colors are determined as high-cost areas with higher conforming loan limits. The match between the color and the limit is listed on the right side of the figure.

Table A1: **Variable definitions**

Dependent variables	Description	Data Source
Jumbo approval rate (count)	The fractions of approved jumbo loan applications to total jumbo loan applications across all lenders in county i and year t, where the fractions are based on approved jumbo loan counts	HMDA
Jumbo approval rate (volume)	The fractions of approved jumbo loan applications to total jumbo loan applications across all lenders in county i and year t, where the fractions are based on approved jumbo loan volumes	HMDA
Rate Spread	The price data take the form of a "rate spread". Lenders must report the spread (difference) between the annual percentage rate (APR) on a loan and the rate on Treasury securities of comparable maturity - but only for loans with spreads above designated thresholds. So rate spreads are reported for some, but not all, reported home loans.	HMDA
NPL/Family loans	1-4 family loans 90 or more days past due plus loans no longer accruing interest/total 1-4 family loans	Call Report
NPL/Family loans (first lien only)	NPL/family loans calculated only based on first liens	Call Report
Family charge-offs/Family loans	1-4 family loans charge-offs/ total 1-4 family loans	Call Report
Family charge-offs/Loan charge-offs	1-4 family loans charge-offs/ total loans charge-offs	Call Report
Borrower Controls		
Log(Applicant Income)	The average of the logarithm of applicant income reported in HMDA within county i of year t	HMDA
LTI Ratio	The average of the ratio of loan amount divided by reported applicant income within county i of year t	HMDA
Minority Fraction	The fraction of applicants who are minority over all applicants in county i of year t	HMDA
Female Fraction	The fraction of applicants who are female over all applicants in county i of year t	HMDA
Lender Controls		
Log(Assets)	The logarithm of bank total assets	Call Report
Leverage	The bank capital-asset ratio	Call Report
Accounting Profits	Net income to total assets	Call Report
Liquidity	Investment and traded securities to total assets	Call Report
Loans/Assets	Ratio of loans to total assets	Call Report
Deposits/Assets	Ratio of deposits to total assets	Call Report
Deposit Cost	Interest expenses on deposits to total deposits	Call Report
Letters of credit/Assets	Letters of credit in total assets	Call Report
Unused Loan Cmt/Assets	Unused loan commitments in total assets	Call Report
C&I Loans/Assets	Share of commercial and industrial loans to total assets	Call Report
Real Estate Loans/Assets	Share of real estate loans to total assets	Call Report
Securitization Ratio	The weighted average securitization ratio of banks in a given county (weighted by bank market shares), and for each bank the securitization ratio is computed as the total volume of securitized mortgages divided by the total volume of issued mortgages	HMDA
County Controls		
County Income Mean ('000)	County per capita income	BEA
County Income Growth (%)	County per capita income growth rate	BEA
HPI Growth (%)	The housing price index growth rate in year t	FHFA
HPI Growth Lag (%)	The housing price index growth rate in year $t-1$	FHFA

Table A2: **Regional variation in lender responses to uniform CLL increase: robustness checks**

This table shows robustness tests for our baseline regressions to explain the regional heterogeneity of jumbo loan approval rates after the conforming loan limit (CLL) increased in 2006. It is estimated using OLS regressions and the dataset is at the county-year level. Columns 1 and 5 include a linear time trend that is identical across all counties and drop year fixed effects. Columns 2 and 6 include state-specific time trends that allow each state to have different trends in jumbo loan credit supply and drop year fixed effects. Columns 3 and 7 are based on regressions that exclude the lowest income counties (i.e., bottom quartile). Columns 4 and 8 are based on a sample that excludes extreme approval rates (1% of the distribution on both sides). The dependent variable is number-(volume-)based jumbo loan approval rate in columns 1-4 (5-8). *Log(County Income)* is the logarithm of county per capita income obtained from the Bureau of Economic Analysis (BEA). The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. All regressions control for borrower, bank, and county characteristics that are defined in Appendix A. All models include county fixed effects. Columns 3, 4, 7, and 8 also include year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
	Time Trends	State-Time Trends	Excluding lowest income counties	Excluding Extreme AR	Time Trends	State-Time Trends	Excluding lowest income counties	Excluding Extreme AR
Log(County Income)*Post	-0.177***	-0.180***	-0.150***	-0.076***	-0.191***	-0.194***	-0.163***	-0.105***
	(0.025)	(0.025)	(0.025)	(0.012)	(0.026)	(0.025)	(0.026)	(0.014)
Log(County Income)	0.519***	0.556***	0.521***	0.258***	0.575***	0.611***	0.599***	0.359***
	(0.150)	(0.141)	(0.177)	(0.078)	(0.151)	(0.142)	(0.181)	(0.093)
Post	1.820***	1.853***			1.973***	2.004***		
	(0.266)	(0.259)			(0.274)	(0.267)		
Year	0.023*				0.017			
	(0.013)				(0.013)			
Observations	7,506	7,506	5,507	4,509	7,506	7,506	5,507	4,509
Time Trends	Yes				Yes			
State-Time Trends		Yes				Yes		
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE			Yes	Yes			Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.170	0.170	0.235	0.392	0.171	0.171	0.227	0.360